Systemic Risk Transmission:
Visualizing Vulnerability

by

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Submitted in fulfilment of the requirements for the
Doctor of Philosophy
University of Tasmania

2nd October, 2020

Dedication

To my family, both near and far, you are the foundation that keeps me grounded and supports me as I continue to grow. I dedicate this thesis to you all. I hope I have made you all very proud.

Declaration

I hereby certify that the work embodied in the thesis is my own work, conducted under normal supervision. The thesis contains no material which has been accepted, or is being examined, for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made. I give consent to the final version of my thesis being made available worldwide when deposited in the University's Digital Repository, subject to the provisions of the Copyright Act 1968 and any approved embargo.

Your faithfully,

Raisul Islam
2nd October, 2020
University of Tasmania

Preface

Authority of Access

Your faithfully,

Raisul Islam

Statement Regarding Published Work Contained in Thesis

This thesis constitutes collaborative efforts with my supervisors. Chapter 3 is co-authored with former Professor Mardi Dungey and Dr. Vladimir Volkov and, is published in the Pacific Basin Finance Journal (doi.org/10.1016/j.pacfin.2019.101255). Chapters 4 and 5 are joint works with Dr. Vladimir Volkov.

Your faithfully,

Raisul Islam
2nd October, 2020
University of Tasmania

Acknowledgements

I begin by thanking Almighty Allah for his countless blessings in my life and allowing me to complete my PhD journey. This would not have been possible without His mercy and grace. This has been an excellent opportunity to research economics and financial risk management; more importantly, I have learned about conviction, hope, sacrifice and faith and to be thankful for everything I possess.

I am grateful to my late primary supervisor, Professor Mardi Dungey, for her trust and inspiration. Mardi, I am very thankful for your careful guidance, faith in my ability to learn and all the opportunities you have provided me. I am also grateful to my current primary supervisor, Dr Vladimir Volkov, and my co-supervisors, Dr Mala Raghavan and Dr Nagaratnam Jeyasreedharan, for their continual support, perseverance and encouragement. Vlad, I am grateful for your trust in my skills, supporting me in all ways possible and patiently guiding me through the most difficult of times. The phenomenal support I have received from the wonderful supervisors and staff enabled me to materialise what I envisioned many years back.

My sincere thanks go to Dr Joaquin Vespignani for supporting me with his guidance and during my teaching at the university.

To those organisations that provided funding for my research—a PhD Scholarship from the Tasmanian School of Business and Economics, University of Tasmania; a research grant from the Australian Research Council (ID ARC DP150101716); and grants from the School of Business for funding attendance at national conference and bearing the costs of publications—thank you for the opportunities without which I could not have been able to complete this research.

Capstone Editing provided copyediting and proofreading services, according to the guidelines laid out in the university-endorsed national 'Guidelines for Editing Research Theses'.

I cannot give enough thanks for the exceptional support I received from my incredible family. To my amazing daughter, Fiona Jannati, I commenced my PhD research when you were only one year old. Through all the obstacles and difficulties that come with PhD study, you have been the force keeping me sane and confident. With your unbound love, you escalated my conviction and focus.

To my beautiful wife, Dr Sonia Sharmin, the waves crashing against the tiny boat that carried us together during this PhD could not reach the end if you did not steer the boat with your sacrifices and faith. There is no limit to dreams when you stand beside me. Thank you for inspiring me and keeping the boat afloat, against all those odds. Thank you for taking care of both of us.

The sacrifices we made and the difficulties we faced were colossal, but we rode through them holding each other close. Thank you for blessing me with your love, Dr Sonia Sharmin and Fiona Jannati. Thanks to my father, MD Quamrul Islam, and my mother, Mahbuba Akther Jahan, for their love, support, sacrifice and encouragement throughout my candidature. I am also thankful to my father-in-law, AKM Shamsul Alam, and my mother-in-law, Shahnaz Begum, for their continual support and encouragement. I am thankful especially to my mother, Mahbuba Akther Jahan, and mother-in-law, Shahnaz Begum, who stayed and helped us in all ways possible, overlooking their deteriorating health. I am thankful for the paramount sacrifice

they made being away from their only grandchild, which inspired and fuelled my conviction.

You all reinforced my spirit from the beginning. This work is a testimony to the strength, determination and resilience of that very spirit.

Abstract

In just over 20 years, due to heightened globalization, the world economies have experienced over 30 widespread crises, stunting growth and employment, among other things. The many financial innovations that followed each passing cycle of a crisis, brought newer means of facilitating higher systemic risk, and the potential for newer contagion to be mired deep into the system. This poses an ever-growing challenge for investigators while naturally triggering higher research interests in this domain. This thesis, addresses some long-standing questions stemming from the systemic risk and contagion literature. The thesis presents a critical review of the relevant systemic crisis literature (Chapter 2) and focuses on the limitations and gaps in the extant literature. The following three concerning issues are identified:

1. Does the emerging picture during a crisis breakout show a common pattern to past episodes?
2. Can we disentangle sources of potential crisis from the intricately complex web of connections across international equity markets?
3. We progress to examine whether investors' risk preference induces a crisis and to what extent such predictors may indicate a pandemic?

We progress gradually by addressing each of the above mentioned issues and proposing means for regulators and managers of risk to contain risk well before a crisis erupts.

The first of the thesis essay (Chapter 3), develops a means of visualising the vulnerability of complex systems of financial interactions globally, using neural network clustering techniques. We aim to investigate 'if the emerging picture during a crisis breakout shows a common pattern to past episodes?' We show how time-varying spillover indices can be translated into two-dimensional crisis maps. These crisis maps have the advantage of depicting the changing paths of vulnerability, including the direction and extent of the effects between source and affected markets. We develop these crisis maps using equity market data for 31 global markets over the period 1998-2017. In this chapter, our aim is to convincingly implement means by which managers of systemic risk can simulate the effects of alternative intervention paths in a network and have some knowledge of where the most effective interventions may lie.

The second essay of this thesis (Chapter 4) differentiates between 'good' and 'bad' interconnectedness by showing how signed spillover measures capture additional information compared to the unsigned spillovers. This builds the framework to address our second concern as 'we disentangle sources of potential crisis from the intricately complex web of connections across the international equity markets.' We analyze the behaviour of 30 global equity markets and compute multiple spillover measures using daily data over the period 1998-2017, which encapsulates many large and small crises. We use the signed realised volatility estimates to distinguish the contagious markets from the interdependent markets. Instead of relying on ex–post-crisis information, we allow our model to identify crisis periods. It is clear the model efficiently detects crisis and newly emerging contagion in the system.

The third essay of this thesis (Chapter 5) develops a means of visualising the vulnerability of complex systems of financial interactions, resulting from the changing risk tolerance of investors. As such, the investors' risk behavior contributes in the buildup of vulnerability in crisis and in calm periods. In this chapter, we'examine if investors' risk preference induces a crisis and if yes, to what extent such predictors may indicate a pandemic ?' We show how both time-varying risk tolerance and spillover indices can be translated into two-dimensional information transmission and crisis transmission maps, respectively. Taken together, the information transmission maps have the advantage of proposing predictions to potential crisis transmission pathways in the crisis transmission maps. These maps provide easily digested visualization showing how information transmission predates crisis transmission, drawing from conditional signed spillover and risk tolerance indices computed from the equity market data for 31 global markets spanning from 1998 to 2017. Brought together, these approaches may help policy-makers and intermediaries take appropriate steps to subdue a crisis before it emerges.

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List of Abbreviations

ABCP	Asset-backed commercial paper
AC	Asian crisis
ANN	Artificial Neural Network
BMU	Best matching unit
BRIC	Brazil, Russia, India and China
DYCI	Diebold and Yilmaz connectedness index
EC	Export crisis
GC	Greek crisis
GFC	Global financial crisis
GIIPS	Greece, Italy, Ireland, Portugal and Spain
GVD	Generalised variance decomposition
MES	Marginal equity shortfall
MHD	Multivariate historic decomposition
OED	Oil exporting developed
OEE	Oil exporting emerging
PRC	People's Republic of China
ROK	Republic of Korea
SES	Systemic expected shortfall
SIFI	Systemically important financial institution
SOM	Self-organising map
SVD	Signed volatility decomposition
UK	United Kingdom
USA	United States of America

Chapter 1

Introduction

1.1 Motivation

We define systemic risk as the risk underlying intertwined financial entities and markets, and it amplifies as the participants continue to weave more risks. Modern network analysis can accurately capture these systemic risk patterns; see for example Allen and Babus (2009); Gai and Kapadia (2010); Acemoglu et al. (2012). Capital flights and the cross-holdings of assets corresponding to investors' changing risk appetite can be the initial string across the gaps in the nodes of a systemic financial network. As systemic risk exacerbating, the distance between the nodes is naturally reduced, a process involving important financial institutions, financial markets and financial products across many sectors and multiple economies.

Interestingly, systemic risk presents the two dimensional surface that allows contagion to form and spread systemic crisis across different regions. However, what builds a surface is not a simple phenomenon.

A crucial condition for contagion to materialize involves vulnerability implicit in systemic connections (Dungey and Martin, 2001). Despite this, systemic risk and contagion guide two different tenets of studies. As we can observe, it is not easily conceivable to tailor systemic risk and contagion under the same model. This also causes the most significant limitation in most studies concerning systemic risk and contagion.

With the heightening of globalisation comes an increased flow of capital across the financial sectors of countries of many sizes and capacities (Islam, 2014a). While participating financial markets and institutions are driven by credit growth the ever-increasing interdependencies drawing intricate networks resemble the structure of a complex spider web. However, the core peripheries of this web spawned from the financial sector representative of an advanced country may not be identifiable as coming from advanced countries themselves. Hence, a random shock may emerge in any of the core peripheries sending vibrations across the web. With each occurrence, there are potential alterations in the position of the core peripheries, making it increasingly challenging to track potential sources of the next shock. This, it is of no surprise, that the disproportionate size of financial sector participants within these networks cause the position of global financial markets to be untenable.

In just over the 20 years, the global economies have experienced over 30 widespread crises, stunting, among other things, growth and employment; see Table 3.2 for more details. The many financial innovations following each passing cycle of a crisis, bring about newer means of facilitating higher systemic risk, and the potential for newer contagion to be mired deep into the system. Moreover, a complete network is not a necessary condition for contagion to unfold; a sparsely connected network holds sufficient for a crisis to spawn and spread; see Dungey et al. (2020). Hence, this domain poses an ever-growing challenge for investigators while naturally triggering higher research interests.

The newly emerging crises are spurring research and creating discourse to an extent not observed before. The contributions in this domain present techniques in many fields, including economics, epidemiology, computer science, physics and engineering. Despite providing a platform for investigators to test the efficacy of their models, the long-standing questions remained unanswered by the extant literature; such as finding predictive patterns in a global crisis and as systemic risk sourcing such a crisis. Commentators have separated systemic risk and contagion apart, and immersed themselves into combining numerous factors that has ultimately led to any one of the concerns; see Table 2.1. This has, in turn, resulted in investigators looking away from discovering a continuum producing predictive patterns. While most studies remain in the ex-post-crisis tenet, the extant literature drifts away from finding a common causation or prediction that may enable regulators to stop an imminent crisis.

After carefully reviewing many articles we observe that the extant literature is fraught with limitations. While some studies have covered a specific crisis, others have selected few financial institutions to address a widespread crisis. Such a micro-level approach may provide a granular view into one particular event ex-post, and is not sufficient to model macro-level risks lying dormant in other institutions. Therefore, inferences are often tentative and speculative when it comes to assessing the overall effect of a crisis. For example, the coupling of markets do not always lead to asset depreciation. Similarly, while some studies have focused on endogenous cycles specific to one periphery, the risks found within the global linkage have been overlooked. Regarding 'global' approaches, often well-developed indicators relay varying messages specific to each crisis that effects the peripheries in different ways. Moreover, the coupling of markets as a crisis ensues does not always lead to asset depreciation.

1.2 Objectives of the thesis

After critically reviewing many papers relevant to the crisis literature, important gaps were found concerning crisis identification and modeling. The extant literature draws on a preconceived notion of crisis sourced from specific identifiers that often failed to provide insights into crisis transmission and associated risks within a system (Acharya et al., 2012; Khandani et al., 2013a; He and Krishnamurthy, 2014a; Bonaldi et al., 2015).

There is a lack of synergy in the studies concerning micro and macro-prudential goals, resulting in differentiating opinions concerning systemic risk or contagion. This gives rise to a contentious debate about whether contagion or systemic risk studies may suffice to explain crisis. This is conducive to roll out studies identifying crises without having to address major issues, such as those found within financial networks, feedback loops, securitisation or, investors' risk tolerance that are naturally built into the systemic risk and systemic crisis literature. This lack of synergy greatly affects the primary focus of these studies, which is to identify a continuum that draws a predictive pattern in crisis that may enable the authority to impede the growth of a crisis. This echoes the concerns partially raised in Duffie (2013); Romer and Romer (2015); Darolles and Gourieroux (2015); Dungey and Renault (2018) etc.

Based on the aforementioned gaps, this thesis investigates patterns in crisis propagation, and aims to identify more contagious sources compared to neighboring markets in the pre-crisis, crisis and post-crisis periods. The thesis further aims to ensure consistency, by attempting to disentangle crisis effects from a single data source. This is because, potential indicators from various sources often lead to disproportionate outcomes in terms of intervention strategies (Kapadia et al., 2012). Also, the thesis provides evidence of agents' changing risk tolerance contributing to the development of crises. Additionally, the thesis attempts to propose a system of patterns predicting an imminent crisis with the potential to turn into a pandemic, while also addressing the symbiotic relationship between systemic risk and systemic crisis or contagion.

The objectives of this thesis are as follows:

1. **Investigate the changing dynamics in systemic risk and dynamic networks spanning across important global financial markets**
   The objective is to investigate 30 episodes of crisis over two decades, spanning across major economies, including the restructuring of intricacies between the financial markets. There is a resurgence in studies focusing on the changing dynamics in market interconnections, but it is also important to understand the evolution of market intricacies with filtered networks. **The objective is to discuss** the effects of such changing interactions in amplifying or dampening the vulnerability of international stock markets corresponding to different episodes and the interventions that follow. Specifically, **this will provide insights into** how differently a common episode affects advanced markets compared to emerging markets, and how such innovation leads to the evolution of the concerned markets in terms of resilience or vulnerability.

2. **Detect a pattern in crisis transmission over two decades of crisis episodes**
   The objective is to identify a potentially common pattern in systemic crisis transmission across all international stock markets over at least two decades. It seeks to visualise an anticipated crisis transmission pathway along a two-dimensional plateau that may correspond to emerging crises. It also aims to detect potential feedback loops preceding crisis episodes, setting the stage for a novel early detection technique. This objective differs from studies concerning stress testing or risk topography in classifying crucial episodes and indicators. Rather, **this objective focuses on** proposing patterns that regulators can simulate and intervene to divert the pathway and avoid setting off a crisis.

3. **Examine the turning off of network links to help deter crisis**
   The aim is to investigate the implications of turning big links off in the dynamic networks described earlier. It re-evaluates market dynamics, removing major sources of important episodes and providing evidence of the repercussions of such policy actions. At the onset of a crisis, a natural response is to

impose restrictions on specific asset classes or cross-border assets in an attempt to decouple from source markets. Therefore, **it is important to examine** if such a response heightens or reduces vulnerability, and the importance of specific peripheries to each node in the system and the balances they bring about.

4. **Examine the efficacy of a novel signed spillover framework to model crisis**
   The objective is to prove whether signed risk measures are better suited to model crises compared to popular Diebold and Yilmaz (DY) risk measures. It examines market dynamics across all episodes of crisis and compares the derived signals with actual events juxtaposed against popular DY risk measures. The purpose of presenting such a comparison is to detect misidentifications in contagion parameters gauging from just one framework. Presenting multiple similar frameworks provides evidence of the robustness of one compared to another. Hence, **it is important to** discover whether running multiple relevant risk analysis frameworks may have important implications in understanding the degree and direction of crisis.

5. **Detect sources of crisis across past episodes by separating contagious markets out in a single framework**
   The aim is to detect major contagious markets in the past and newly emerging contagious markets within a single framework. **A major gap in the extant literature is the effect of 'interdependence', as it is often enveloped within the potential effects arising from 'contagion', leading to bias resulting from heteroscedasticity and, often, failure to adopt an appropriate policy response to an imminent crisis**. Interdependence bears a less negative connotation compared to contagion, but to date, the voluminous literature has not incorporated major perspectives into crisis studies, resulting in many incomplete crisis examinations. Among the 124 studies reviewed by Seth and Panda (2018), only four studies mentioned contagion, interdependence and integration. Forbes and Rigobon (2002) proposed separating contagion while considering temporal increases in contemporaneous volatility jumps. However, this was revisited only recently by Dungey and Renault (2018), who suggested incorporating the heightening of volatility jumps as common factors in both 'source' and 'target' markets, which often obscure the effects of contagion from the 'source' markets. **Here, the objective is to employ a single framework to model crisis, while also capturing the contagious markets out. Further, this method, is not obscured with transitory spikes in volatility.** Identifying contagious markets both ex-ante and ex-post assists risk regulators and managers to devise better strategies to cushion against potential market falls.

6. **Propose an early warning approach based on early crisis detection along with investors' perceived risk and changing dynamics of the market**
   The aim is to propose an early crisis detection technique to provide regulators with better tools in managing risks and vulnerability, with the underlying hypothesis that news transmission predates crisis transmission. Here,

investors' risk tolerance matrices are a proxy to news transmission, which helps in producing a news transmission pathways to compare against a crisis transmission pathways in a two-dimensional plateau. To explain this, the literature has used stochastic general equilibrium models, agent-based models, and rational expectation theories. While earlier models attempt to simulate 'frictionless' markets by avoiding crisis as a factor, later models assume investors to make rational decisions. Past crisis episodes are rife with overconfidence and fear, often in the presence of incomplete or asymmetric information, which fuels an ensuing crisis. **The thesis addresses these concerns**, and models the dynamics in signed risk tolerance corresponding to signed risk matrices. It also produces predictive visual patterns to examine the ability of news transmission to predate a potential crisis transmission pathway in a system comprising an intricate web of international markets. **Here, the objective is to** understand if investors show calmness or aggressiveness in the different phases of crisis building before its outbreak.

1.3 Structure and key contributions

In this thesis, we address several long-standing questions identified within the literature. A highlight of the crucial issues we address in this thesis is as follows.

1. **Chapter 2: Literature review**
   In this chapter, we present a critical review of recent papers from the systemic crisis literature. **We identify gaps in the literature** encompassing systemic risk, securitisation, feedback loops, financial contagion, financial network, dynamic risk tolerance, and news/information transmission. A conservative case of minor crisis reflects all factors found across stream of studies; consequently, a careful diagnosis of the gaps identified from the literature is discussed in this chapter.

2. **Chapter 3: Systemic risk - visualising vulnerability**
   In the third chapter, we respond to objectives 1, 2, and 3 mentioned earlier. We propose a new way to visualize the contagion transmission pathway:

   - We begin by examining the time-varying nature of systemic risk found within global equity market interdependence spanning over two decades. Instead of focusing on an ex–post-crisis, we allow our framework to model crises highlighting both ex-ante and ex–post-crises development. This also allows us to investigate the changing degree of emerging risks and the associated policy responses attempting to stem a falling market. Our sample includes countries of different sizes, allowing us to acknowledge the conditional nature of the problem and its different effects of the peripheries.
   - We estimate transmission and vulnerability indices, focusing on which markets are more resilient and under what conditions. This allows us to understand the evolution of the equity markets that face innovations sourced from others, which has heterogeneous market effects. We draw networks from risk gauges by observing the peripheral position of markets

to each other. We postulate the susceptibility of each market to its core peripheries facing a major crisis event.

- Next, we turn the linkages off to examine if such a situation would attenuate a crisis propagation across markets. This will also explain how important the third and fourth-order peripheral markets are in either attenuating or precipitating a crisis.
- Then, we produce novel, dynamic pathway maps for crisis transmission, highlighting the contagion pathways that may also evolve. This is analogues to a brain scan lit up by firing neural pathways and visualise a potential pathway for global contagion. Such a method will allow regulators to simulate alternative intervention pathways and identify the most effective intervention according to where a specific crisis lies. Most importantly, we seek out specific patterns in the contagion pathway in a predefined system, across many markets and over decades to answer the long-standing question, 'Do crises have a common pattern?'.
- We identify the forming feedback loop patterns appearing across the dynamic maps, and visualise the predictive power of new feedback loops, which induce newer crisis cycles across peripheries. Hence, detecting new feedback loop indicates the first stage of an ensuing crisis.

3. **Chapter 4: Contagion or interdependence- comparing signed and DY spillovers**
   In chapter 4, we respond to objectives 4 and 5 mentioned earlier. Following on from Chapter 3, we propose a novel signed volatility decomposition (SVD) approach for contagion identification using high-frequency observations in addition to the data we used for Chapter 3:

   - We begin by examining the evolution of risk matrices based on DY spillover analysis. We compare the popular DY variance decomposition to the newly proposed signed variance decomposition to discover whether more reliable demarcation of crisis periods is possible with signed decomposition. We ensure consistency described in Romer and Romer (2015) by testing the efficacy of our methods against the same data.
   - The simultaneous increase in volatility during a crisis is often wrongly attributed as resulting from contagion. It is because such amplifications in risks pertains to interdependence and overestimates the effect of contagion for a particular market. We propose a tractable, novel, SVD approach, building on the newly proposed signed variance decomposition, which separates the effects of contagion effects from those due to interdependence while offering better crisis demarcation without prior crisis knowledge. The approach is data driven, and does rely on Forbes and Rigobon's (2002) findings on contagion and interdependence.
   - Next, we provide a rationale regarding the recent surge in speculation around crisis sources, and explore whether there is enough evidence aligning with these postulations. Finally, we address some key questions that have long puzzled researchers. Can we extract more contagious markets out of sample clusters? Are these markets generating crisis episodes

drawn towards a continuum conducive to predictive patterns? How diabolic are contagion patterns in more recent times compared to before? Can we disentangle substantially large contagion patterns driving global economies towards a potential crisis?

- Identifying potential sources of contagion and patterns underpinning contagious markets will allow regulators to take timely action attenuating the exposure of domestic markets to a large-scale crisis.

4. **Chapter 5: Calm before crisis**
   In chapter 5, we respond to the objective 6 mentioned earlier. We propose an early warning system that evolves across the methods proposed in the earlier chapters of this thesis. We continue using the same data to ensure consistency in our models and findings:

   - First, we investigate the effects of investors parsing crisis-related information differently. This, in turn, reinforces crisis transmission. We model investors' risk preference corresponding to contagion spanning across the international stock markets.
   - Next, we propose information transmission maps computed from investors' risk preference indices, drawing on data from risk matrices. In proving information transmission predates crisis transmission, we examine information transmission maps juxtaposed against crisis transmission maps. Moreover, the dynamics in investors' risk preference underscore predictions regarding the advent of a crisis. This answers a crucial question: 'Do investors' risk preference work as an early warning predictor for economic crisis?' In other words, to impede crisis propagation, it is important to understand whether the dynamics in investors' risk preference induce a crisis. Wherever applicable we use vulnerability and risk dynamics (risk tolerance, risk preference, risk sensitivity and aggregate risk behaviour) interchangeably, referring to degree of amplification and dampening in the crisis transmission and risk aversion index gauged from our proposed framework.
   - Finally, while unprecedented changes in the intricacies of financial markets make it almost impossible to impair a crisis, regulators can effectively contain the degree of information transmission within domestic markets. Proving investors' risk preference that trigger a potential crisis will provide a means for regulators to mitigate a potential crisis. Our methods provide a means to contain a crisis well before the crisis unfolds, without having to rely on past crisis patterns.

5. **Chapter 6: Conclusion**
   Progressing gradually from the first to the final chapter, we intend to propose a common solution to the issue of contagion.

In what follows, we discuss important studies on systemic risk and contagion, the limitations in the extant literature and the many facets of the problematic. Then we present the findings from each of the chapters before concluding the thesis.

Chapter 2

Literature review

In the wake of the Global Financial Crisis (GFC), the intertwined economies that attempted to attenuate the spread of the crisis sparked research in the field of crisis transmission. This field comprises research into contagion, such as the early work of Allen and Gale (1998), and shock spillover, which includes even earlier studies like King et al. (1994). The crisis transmission literature expands further to include natural experiments in financial networks proposed by Allen and Gale (1998) and Gai and Kapadia (2010), which are either reinforced or attenuated when faced with an imminent crisis. While Allen and Gale (2000) and Gai and Kapadia (2010) investigated networks existing within financial sectors, Acemoglu et al. (2015) pointed out that the changing levels of connectivity between the network nodes, turning 'robust' interconnections into 'fragile' ones, create a large enough economic shock to spread through the networks and turn into a major crisis cycle termed contagion. With the advent of new empirical approaches in the field of network finance came the demarcation of crisis periods from, for example spillover gauges (Billio et al., 2012; Khandani et al., 2013a; Diebold and Yılmaz, 2014; Dungey and Gajurel, 2014; Dungey et al., 2017a, 2019). More recently, investigators have been able to solve crisis patterns even from the sparsely connected networks, see for example (Dungey et al., 2020). *Therefore, the efficacy of these methods is the key to identifying systemic risk in the interconnected nodes and, by extension, contagion.*

Elliott et al. (2014) argued that globalization and the ever-increasing level of interdependence between various sectors in an economy are the driving factors for economic progression. A primary concern is that such an unprecedented increase in interconnections can lead to a cascade, a process that involves equity or debt markets, banks and other depository, investment and even non-financial institutions. However, what is arduous is the identification of the key players due to constantly changing architecture of this intricate web of connectivity (Dungey et al., 2018b). Thus, there is increasing research into the forces driving such connectivity to defuse these cascades in an economy and, for that matter, all other peripheral economies connected to the origin, see Table 2.1. Such studies are crucial, as understanding the risks channelled within the integrated nodes of markets and institutions provide a means for policy makers to steer responses and incentives towards ameliorating the risk of a complete economic failure (Anufriev and Panchenko, 2015). What is more threatening is that, often such risks generating from random shocks sourced from a distant, hidden entity (Dungey et al., 2010a).

A key statement in the voluminous literature, which has generated several avenues of discussion regarding crisis control, is the heightening of integration resulting from modern globalization, which is what causes contagion and systemic failures; see for example, Atsalakis and Valavanis (2009); Bisias et al. (2012); Chinazzi and Fagiolo (2015); Benoit et al. (2017); Silva et al. (2017); Seth and Panda (2018). In the absence of integration and interdependence, there is no shock transfer sourced outside and the probability of a large-scale cascade is minimised. From the perspective of an entity, such as a financial institution or a financial market, exposure to identifiable or non-identifiable risks stems from dynamic integration, as integration leads to financial entities' dependence shifting away from its holding of its own primitive assets (Bisias et al., 2012). This is appealing because it provides investors with not only a sense of higher returns by investing across borders, but also the attenuation of the sensitivity of the portfolio to particularly visible shocks (Silva et al., 2017). Indeed, with the cross holding of assets from diverse entities, shocks that are conspicuous can be averted until they reach a 'sweet spot'. In what follows is a contagion that is so far reaching and out of control that a cascade does not remain within the premises of an entity or a country (Seth and Panda, 2018).

Elliott et al. (2014) described two key conditions that are vital for a widespread crisis to materialise from intertwined financial markets. First, even a sparsely connected network may bear the potential of a widespread crisis. Each entity holds a sufficient quantity of its own asset for it to spark a crisis preceded by an idiosyncratic shock to the value of assets held. Further, each entity must hold enough cross assets to enable that shock to spread as it transpires. Second, the extent to which network connections exist are fragile enough for an instantaneous propagation of shock, but not robust enough for the connections to be well insured against potential in-shocks emitting from counter-parties.

These conditions lead to important suggestions regarding natural experiments in empirical economics. One such suggestion is the trade-off in diversification and integration that results in non-monotonic effects and causes alterations in network structures and its core-periphery (Acemoglu et al., 2012). This provides a fertile ground for empirical examination using new parametric identifications facing any new event. Elliott et al. (2014) proposed a tractable approach to interconnectedness basing on simulated results and suggested that the changing degree of connections in a network may sufficiently blunt a large enough crisis. Earlier, Shaffer et al. (1994) identified that systemic failure often corresponds to risk sharing between entities. Holding portfolios with similar assets increases the probability of a large shock, which brings down common assets along with the bearers of such asset portfolios who belong to a combined network. Further, Gai and Kapadia (2010) pointed out that due to the non-monotonic nature of a financial crisis, depending on where in a network it is hit by a large economic shock, there can be a disproportionate outcome for nodes in a combined network. Moreover, the effects can turn catastrophic given the dynamic position of the 'point of hit' in a spherical network. This is in line with the findings of Ibragimov et al. (2011) and Allen et al. (2012). Thus, by aiming to identify the 'sweet spots', using counterfactual experiments on random sets of underlying asset prices or a set of nodes in a network, it is possible to discover the more susceptible alliance structures under different scenarios. *Therefore, the next question is, With this information, can the links be altered to diffuse a potential crisis?'*

We contend the argument aiming at the trade-off between diversification and integration. We believe the issue of financial crisis require a balanced combination of arguments across streams of studies concerning financial crisis, systemic risk, securitisation, equity and banking risk argument, feedback loops, financial contagion,financial networks, risk perception subject to changes in information and risk topography. A visual connection between these streams of studies are presented in the Figure 2.1, Figure 2.2, Figure 2.3 and Figure 2.4. Such a balanced discussion reduces the limits of diversification while retaining the current degree of integration.

2.1 Crisis literature

The fear of an economic shock reaching the 'sweet spots' has been justified in many crises, particularly those occurring in the last two decades compared to those in the the preceding decades (Elliott et al., 2014). The casting off of risks borne out of interconnections is fuelled by preceding credit booms, unprecedented global economic booms coupled with exacerbation in leverage build-up. Thus, in just two decades, the many facets of risk lying dormant in intertwined financial entities stem crises of many sizes and directions (e.g., Asian financial crisis, Russian debt crisis, Japanese economic stagnation, dotcom bubble, global energy crisis, subprime lending crisis, GFC, European debt crisis, Russian ruble crisis and Chinese stock market crash). These crises had disproportionate effect on each of the participants in the global economy, spurring research into identifying the changing roles of national financial markets and other major entities contributing to the build-up of each crisis sourced from different points. Interestingly, these forces are blunted with good policy responses, which may also be responsible for the build-up of new crises (Raghavan and Dungey, 2015).

In Seth and Panda's (2018) review of 151 papers focusing on contagion, spillover and integration, 59 papers were found to focus on the Asian financial crisis, 48 focused on the GFC, 20 reported on the subprime lending crisis, 28 detailed the European debt crisis, 23 focused on the Russian debt crisis, 22 on the tequila effect and six on the World Trade Center terrorist attack and subsequent war. It is apparent that research into contagion conveniently separates the Asian and global financial crises preceded by the subprime lending crisis and European debt crisis. The Asian financial crisis of 1997-1998 began in Thailand and spread to neighboring countries, including Malaysia, Singapore, China, South Korea, Indonesia and the Philippines, providing fertile ground to experiment with crisis policy responses (Raghavan and Dungey, 2015). The countries in this particular crisis are discerning in size, financial culture, economic stability and level of financial collaboration, and following the widespread crisis, each country implemented contrasting policy responses. For example, Malaysia fell back into fixed exchange regime, while both South Korea and Indonesia floated exchange rates (Khan and Park, 2009). Interestingly, both China and Singapore retained their existing policies and averted the worst of the crisis very well, as suggested by Raghavan and Dungey (2015). Notably, the effects of the crisis were felt beyond the national boundaries of the aforementioned countries, which we aim to identify and focus on.

A major cascade, especially in the equity markets, is associated with the unfolding of an event like war. Leigh et al. (2003) and Rigobon and Sack (2005) concurred that what preceded the collapse of equity prices in the United States of America

(USA) was the anticipation of a long-term engagement in the Iraq War. Further, Schneider and Troeger (2006b) suggested that war invokes heightened systemic risk and interconnections, as investors parse war related news differently, contributing to the amplification of capital flights. This was vindicated by the downfall of many stock markets with the increasing possibility of an Iraq invasion. For a 10 per cent increase in the probability of an Iraq invasion, Leigh et al. (2003) estimated a ≥ 3 per cent price drop in the equity markets in Germany, Israel, Hong Kong, Taiwan, Venezuela and, Sweden, a 2–3 per cent price drop in the US, China, The United Kingdom (UK), Russia, France, Canada, Norway, Singapore, Portugal, Netherlands and, the Philippines, and a ≤ 2 per cent drop in Australia, Belgium, Greece, Japan, India, Malaysia, Sri-Lanka and Indonesia. While prolonged wars could unfold the sources of some major financial contagion (Leigh et al., 2003), encapsulating war engagements in studies is more or less fashioned arbitrarily .

It is conceivable that the impending military invasion in the Middle Eastern region resulted in the removal of capital in the equity markets of advanced countries and may have led to a downward spiral in the major developed economies. Exacerbation of this economic dampening with the continuing war is conducive to a global financial contagion. However, was the build-up of the GFC due in part to a contagion caused by war participants? This is shown in the downward spiral of the Japanese and European stock markets alongside the recession in the USA (Leigh et al., 2003). Despite buoyant Japanese and European markets blunting the forces of contagion during the Vietnam War, the Iraq War led to contraction and suspension of the oil market (Schneider and Troeger, 2006b). The petrocurrency effect, coupled with the already stricken financial sectors in Japan and the European Union, escalated the crisis, which propagated from the USA recession to the other participants in a complete network. As the major economies were sent into a downward spiral, a more protracted recession penetrated deep into the economic and financial architecture. We conjecture, in the ensuing eurozone crisis from deep within the European network, the tremors were heavily felt in the nodes outside the European network. To better understand the patterns emerging at specific points in time, it is essential to disentangle the effects of contagion and systemic risks out of equity market upheavals.

Muir (2017) distinguished between the effects stemming from a financial crisis recession, deep recession and war events and investors' expectations regarding asset values, risk premiums and liquidity in the international stock markets. In the vast literature, financial crisis is defined as build-up of systemic risk corresponding to a banking crisis (Shrieves and Dahl, 1992; Sbracia and Zaghini, 2003; Lepetit et al., 2008; Allen and Carletti, 2010; Puri et al., 2011; De Bruyckere et al., 2013a; Kalemli-Ozcan et al., 2013; Dungey and Gajurel, 2015). Muir (2017) argued that risk premiums are a more dominant factor than capital during a financial crisis, indicating equities are better determinants of a crisis. Moreover, a bank's liquidity buffer dampens during a recession, deep recession, war-related events and financial crisis alike, creating confusion regarding separating the effects from financial crisis alone. Only swings in the risk premiums are collinear to the degree of financial crisis. Notably, Muir (2017) pointed out that immediately after a crisis, realised returns increase, reversing the drag on wealth; however, this is unlikely in a recession.

Since the last decade, the tremors originating from many major crises have driven investigations concerning elements of their contagion and systemic risk. The crises that have attracted the concern of more commentators include the Mexican crisis (Tequila effect) of 1994, Asian financial crisis of 1997-1998, Russian bond crisis of 1998, subprime crisis of 2007, GFC of 2008 and European sovereign debt crisis of 2010. For the most part, studies tend to concentrate more on the three recent crises (i.e., subprime crisis, GFC and European sovereign debt crisis). These studies include Ye et al. (2016); Hemche et al. (2016); Lin et al. (2015); Flavin and Sheenan (2015); Anderson et al. (2015); I. Dimitriou and M. Simos (2014); Chittedi (2014); Hoesli and Reka (2013); Dimitriou and Simos (2013); Gallegati (2012); Celık (2012) and Dooley and Hutchison (2009), which focused on the subprime crisis only. Similarly, Fry-McKibbin and Hsiao (2018); Jin and An (2016); Pan et al. (2015); Luchtenberg and Vu (2015); Kim et al. (2015); Kenourgios and Dimitriou (2015); Mollah et al. (2014); Jung and Maderitsch (2014); Islam (2014a,b); Gammoudi and Cherif (2014); Dungey and Gajurel (2014); Choudhry and Jayasekera (2014); Mighri and Mansouri (2013); Kenourgios et al. (2013a,b); Guesmi et al. (2013); Dimitriou and Simos (2013); Neaime (2012); Min and Hwang (2012); Samarakoon (2011); Kazi et al. (2011); Guo et al. (2011); Chudik and Fratzscher (2011); Aloui et al. (2011) and Moosa (2010) concentrated on GFC only. Gómez-Puig and Sosvilla-Rivero (2016); Jayech (2016); Shen et al. (2015); Glover and Richards-Shubik (2014); Chira and Marciniak (2014); Ahmad et al. (2014, 2013); Kasch and Caporin (2013); Beirne et al. (2013); Mink and De Haan (2013); Arghyrou and Kontonikas (2012) investigated just the European sovereign debt crisis. The studies that examined both the GFC and the European debt crisis include Yang et al. (2016); Rotta and Valls Pereira (2016); Mollah et al. (2016); Tabak et al. (2016); Bartram and Wang (2015); Kenourgios and Dimitriou (2015) and Kazi et al. (2014). Notably, the studies listed above do not present a complete collection contagion, spillover and interdependence literature, but rather provide a pattern focusing on specific crises.

Seth and Panda (2018) summarised most of the existing literature focusing on the Asian and global financial crises, the more recent of which focus on European debt crisis, but even more so on the GFC. In their review, Seth and Panda (2018) reported that 80 per cent of the global literature centred on these few crises. Moreover, 50 per cent of studies examine only one or two crises, while as little as 2 per cent of studies capture crises spanning across a period of two decades.

How does a financial crisis build-up and what cycles precedes it? The crucial literature pointed out that excessive credit growth precedes a crisis (Kaminsky et al., 1998, 2003; Reinhart and Rogoff, 2009, 2011). In defining liquidity spirals, financial cycles and leverage cycles Tobias and Brunnermeier (2016); Drehmann and Juselius (2014); Borio (2011); Brunnermeier et al. (2009) and Reinhart and Rogoff (2009) pointed out that the removal of capital reserve leads to excessive credit growth. Insufficient reserve to provide a buffer of resources in a downturn exacerbates such a credit boom. At this point, highly risky credit is issued that is held by financial institutions with little or no buffer of resources in the event of a crisis. Consequently, following a tractable credit cycle, the boom goes bust as depicted by Engle (2018). In response, managers and regulators attempt to deleverage and de-risk financial sector institutions by selling off equities and assets in large quantities. Indeed, the resulting contraction in asset prices leads the sector into a process of downward is called fire sale externality, which has been examined by Cont and Schaanning (2017); Greenwood et al. (2015) and Brunnermeier et al. (2009). The situation worsens when there are not enough willing buyers, which contributes a large scale crisis across the entire economy.

2.2 Systemic risk

It is important to understand that connectedness measures at large do not indicate risk transmission, but identifies the degree of systemic connections, in our case, across borders. Systemic risk transfer within borders may not lead to a full scale crisis, but risk transfer across borders, as Brunnermeier et al. (2016) suggested, may indicate a diabolic loop, or as highlighted in Farhi and Tirole (2017) a deadly doom loop creating a large scale crisis. While contagion measures may capture only the volatility spillovers as suggested in Masson (1998); Khan and Park (2009); Bekaert et al. (2013), that may emerge with large shocks spilling over onto the neighbors corresponding to an event, that is not likely be a systemic event (Dungey and Renault, 2018). We aim to identify the spillovers originating from high degree of systemic risk build up and both the ex ante and ex post development of systemic crisis. This leans more toward financial network studies that is made popular by Dungey et al. (2010c); Billio et al. (2012); Khandani et al. (2013b); Anufriev and Panchenko (2015); Acemoglu et al. (2015); Dungey et al. (2017b); Demirer et al. (2017) presented in the first half of the paper. This discussion leads to visualization of risk topography approaches of such found in (Duffie, 2013). Duffie (2013) proposed a 10 by 10 by 10 approach, whereas we progress with a 31 by 30 by 30 approach in chapters 3 and 5, and as such proposes a novelty into the thesis.

Extant empirical work explored the buildup of systemic risk in growing markets, which experience pro-cyclical credit buffers and financial crises of varying sizes (Dungey et al., 2013b, 2007; Antonakakis and Vergos, 2013; Claeys and Vašíček, 2014). The changes in networks between markets following a crisis period may result in higher shock spillover than previously observed (Acemoglu et al., 2015; Dungey and Tambakis, 2005; Dungey et al., 2007), some of which may be a consequence of bubbles fueled by credit expansion and associated build-up of macroeconomic vulnerabilities (Kaminsky et al., 1998; Alessi and Detken, 2009; Drehmann et al., 2010; Drehmann and Juselius, 2014). The recessions resulting from the burst of bubbles are relatively deep and protracted, and features a slow recovery (Jordà et al., 2013; Hermansen and Röhn, 2017).

Cyclical swings in credit conditions lead to varying degrees of crises stemming from systemic risks in the interconnected capital markets (Gonzalez et al., 2017). In turn, this has led to concerns over means for reducing the pro-cyclicality of prudential and capital market regulation (BIS, 2010a,b). Basel III has been criticized for failing to address the pro-cyclicality of stock markets and crises (Saurina and Repullo, 2011). These concerns have led to a heightened interest in how monitoring capital market interconnectedness may help in early detection of buildup in systemic cyclical risks (Hermansen and Röhn, 2017; Kaminsky and Reinhart, 1998; Alessi and Detken, 2009; Bordo and Haubrich, 2010; Drehmann and Juselius, 2014).

In particular, regulators are concerned that the extent to which shocks are amplified across equity markets is directly related to the degree of vulnerability in the network. **We address this problem by examining both transmission and vulnerability in chapters 3, 4 and 5.**

Engle (2018) suggested that a predictor of systemic risk is essential to identify the degree of risks that may lead to any of the cycles described so far in this literature review. Such a predictor provides important information on the level of systemic risk in specific sectors that can be borne by participants before the advent of crisis. For example, Engle (2018) reported that systemic risk is dampening in Europe as the European debt crisis subsides, but that despite mushrooming recently to its highest level in China and Japan, these countries are not emitting a large scale crisis. Thus, an important question at this stage is, **'How are these potential crises being contained, and would other measures produce similar high estimations of systemic risk for China and Japan?'**

The literature reiterates that the regulatory framework is typically micro-prudential, as observed in the lead-up to GFC (Hanson et al., 2011; Fama and French, 2010; BIS, 2010b; Brunnermeier et al., 2009; Kashyap et al., 2004; Borio et al., 2001). For the most part, a micro-prudential study examining factors associated with the largest or benchmark financial institutions, which provides a narrow perspective of the system (Romero-Meza et al., 2015; Krishnamurthy and Muir, 2017a). We present the limitations of micro-prudential studies in Table 2.2. In contrast, a macro-prudential approach identifies potential vulnerabilities in the system. To safeguard the system and attenuate the potential for a crisis, intervening at the fragile points without tilting the system, including understanding how its elements connect or react to changes, inadvertently damages the system and precipitates further crisis.

In the event that multiple financial entities are hit by a common shock, a debilitating phase would follow that Hanson et al. (2011) termed as 'generalized asset shrinkage'. As financial and depository institutions attempt to shrink the balance sheet, the two most obvious social costs emerge: credit crunch and fire sale. As lenders, depository and financial institutions reduce lending to shrink assets, amplifying the price of credit for borrowers. Borrowers respond by cutting down on new investments and limiting employment, driving the economy towards a contraction. Alternatively, financial institutions shrink assets by trying to dump their more illiquid assets, sparking a fire sale. Hence, there is clearly a visible connection between the effects of a fire sale and credit crunch. Stein (2010); Shleifer and Vishny (2010) and Diamond and Rajan (2009) observed that a crisis is exacerbated with the manifestation of fire sales in the deepening credit crunches.

One element that connects fire sale and credit crunch in the lead-up to an economic contraction has been identified by Myers (1977) as the 'debt overhang' problem. Myers (1977) discovered that in a crisis state, a bank with impaired value of its held debt will be reluctant to fund new investments and raise new equities with sure profit. Banks that perceive its senior creditors to generate more value will prefer selling off its assets rather than creating them. A buffer of capital stocks created in calm periods would allow the banks to be more flexible with assets and, more importantly, would allow these institutions to exploit profitable avenues as crisis weakens competition. Stein (2010) explained that a financial institution is reluctant to maintain a capital buffer because it considers short-term debt a cheaper financing option than equity. In doing so, what is overlooked are the risks generated by the bank itself, as it ignores the dampening values of common equities it holds of other banks when a fire sale is triggered. Lacking a safety net, a fire sale is often triggered from these types of entities, which will impede the liquidation value of common assets for the other financial entity. Naturally, a similar cycle will transpire for the other entity, which now bears the full brunt of the shock affecting the first bank. Here is described a vicious cycle that eventually leads to a cascade.

The cycle turns even more vicious when a crisis is triggered not only for a few financial institutions but for an entire market—this is a cascade. Crucially, an equity market crash stemming from a banking crisis gears the economy towards a full-blown crisis. Hence, it is important to identify risks emerging from both financial institutions and financial markets to fully understand the tipping point for a crisis. Stein (2010) described the process of trenching, which may provide a better answer. Most investors interested in buying trenches of asset-backed securities finances their purchases with short term debts. Known as 'structured vehicles', these entities service these debts in the form of commercial papers, which hold and trade asset-backed securities. The debts and the commercial papers mature within a few hours to overnight. Collectively, the process is known as the shadow banking system. Trenching also allows for the AAA rating of a pool of underlying assets, which predominantly subdues the real rating. This attracts more uninformed investors, who often find the costs involved in understanding the complex information to build a pool of assets dulls their incentive to be informed. Chernenko et al. (2013) provided evidence for a large presence of uninformed investors leading to increased financial market vulnerability.

One reason that banks prefer to leverage, forgoing the pursuit of equity generation, is the cost of capital. The 'competition hypothesis' establishes that banks control the cost of capital to the extent that drives the banks away from high-quality, long-term investments towards raising liquidity through issuing or investing in stocks. This is particularly true for banks(Stein, 2010).

The pursuit of short-term debt by larger banks, coupled with the fact that investors seem to attribute little importance to information allows the shadow financial industry to build-up disproportionately for different economies. Consequently, this frequently causes weak spots to emerge in a combined network. This, in effect, sets the stage for an initial tremor from a random shock in the equity market, triggering fire sales by the banks and, by extension, other intertwined financial institutions and markets. This crisis spreads in both directions and, by attempting to siphon off large collaterised debts with fire sales, the banks bring down other common equity prices to build into their debt pool. Uninformed investors respond by moving funds, affecting other participants in the system and sending the economy towards a downward spiral.

Romer and Romer (2015) pointed out several issues that have been identified from the extant literature. First, previous research almost invariably suggests that all crises in consideration affect all countries equally, and they are either moderate or severe in nature. Romer and Romer (2015) suggested that the extent to which a crisis affects an economy depends largely on the size and intricacy of that economy. Advanced economies may experience different effects than do emerging economies (Dungey and Renault, 2018). This is due not only to differences in policy responses and industrial composition, but also to the ability for the less intricate, emerging economies to contain a crisis more effectively than a more intertwined economy (Raghavan and Dungey, 2015). Any reliable conclusion should also be examined not only in the context of holistic networks, but also in the context of sparsity of those networks. In the current thesis, to present dynamic networks, we compared the sample economies as being densely or sparsely connected.

A second issue that has emerged from the the extant literature is the imprecise identification of the constituents of a crisis (Romer and Romer, 2015). What constitutes a crisis may range from asset price decline, bank run-on or, even institutional bankruptcies. Many studies have focused on the financial institution's failure, which inadvertently sources a crisis. However, regulatory forbearance and intervention disproportionately affects the cost of intermediation for banks; thus, these are noisy indicators. Additionally, what impedes the reliability of such studies is a lack of consistency. *Consistency as defined by Romer and Romer (2015), is using single source data over many periods and across many different countries (p.11).* As mentioned earlier, few studies have attempted to address consistency to some degree. We addressed consistency in the current thesis by adopting single source data for multiple, connected experimentation.

Finally, as few studies went beyond classifying between non-systemic and systemic crises (Romer and Romer, 2015), a third issue arises in which explaining crisis using a binary classification obscures the effects of different crises and alters how constituents of crises interact. This leads to inaccuracies, resulting in large discrepancies in the values assigned to multiple episodes of crisis. Failure to explain the different episodes of crisis obliterates a fundamental goal that these episodes may be merged onto a continuum that produces predictive patterns rather than discreet occurrences. Consequently, this impedes reliability in the ex-ante measurement of a crisis. **In the current thesis, we converted these episodes using numerical scales, so that stress levels were examined with 10-base and 900-base classifications.**

Turning to the issue of systemic risks in capital markets, a crisis stemming from systemic risk is maintained by cyclical swings prevailing in capital market (Gonzalez et al., 2017). This strand of the literature examines what impede the build up of such a crisis, a process that involves prudential and capital market regulation (for International Settlements, 2011). Combining solutions from earlier studies, the proposed Basel III did not have the efficacy to attenuate episodes of crises in stock markets in advanced economies (Saurina and Repullo, 2011). This has spurred research into the use of capital market interdependence gauges in early crisis detection (Hermansen and Röhn, 2017; Drehmann and Juselius, 2014; Bordo and Haubrich, 2010; Alessi and Detken, 2009; Kaminsky and Reinhart, 1998).

The perceived increase in risk coming from interconnections during, for example, the GFC, is implicit in systemically important financial institutions (SIFIs) (Dungey et al., 2013a). According to the federal reserve governor, Daniel Tarullo, financial institutions are systemically important if the failure of the institution to meet its obligations to creditors and customers would have significant adverse consequence for the financial system and the broader economy (e.g., Gorton et al. (2010), p.304). This definition stipulates that an under-capitalised institution, regardless of its size and position, cannot trigger a crisis, unless under-capitalisation in all institutions reaches a tipping point. However, by focusing specifically on identifying financial institutions that are the sources of a crisis, it cannot be argued that only capital shortfall spanning across all institutions can lead to a cascade. Both Acharya et al. (2012) and Brownlees and Engle (2016) concurred that during an economic downturn, the effects of the under-capitalisation of large institutions cannot be fully absorbed by others, which imposes substantial negative externalities to the economy. A significantly under-capitalised financial sector precipitates further crisis. Thus, a fundamental question continues to puzzle investigators regarding what comes first: a weak institution or a crisis? Conveniently, SIFIs have been considered the source of a crisis, which is clearly not the case. Acharya et al. (2012) stipulated that while a crisis may be endogenous for a weak institution, this does not imply causality. Thus, these knowledge gaps provide a perfect natural ground to study the actual forces that create a crisis and other avenues, which may provide some insight.

Moving along this route, Wagner (2010) provided evidence of the degree to which diversification of financial institutions across multiple financial sectors affects the dynamics of systemic risk for individual institutions. Intuitively, expecting diversification reduces an individual financial institution's probability of failure and increases its flexibility. Hence, financial institutions unanimously engage in diversifying the assets they hold. Although the immediate value of the assets surpasses the liabilities of each institutions, they are attributed with higher risks, which traces back to the institution's financial integration resulting from diversification. Further, diversification exposes institutions of all sizes to risks that outweigh their own idiosyncratic risks, are purely mechanical and are not induced from contagion. Acharya and Johnson (2007) asserted that banks use diversification to form systemic connections, expecting joint failure will insure themselves against bailouts, while also intentionally engaging in premature asset liquidation during downturns. The forming of SIFIs eventually induces new systemic risks that exceed beyond any one sector. For example, Allen and Carletti (2006) found evidence of spill-backs between the insurance and banking sectors facing a trigger event. Wagner (2010) suggested that to impede the new SIFI formation and reduce systemic risk creation in all institutions, a lack of efficient diversification is needed that is associated with higher regulatory fees, as well as promising no capital relief for institutions attributed with systemic risk.

In Silva et al.'s (2017) analysis of the systemic financial risk literature, a major issue found was the tendency to identify this phenomenon with banking crises. Further, Field (2003) found that this tendency was an underlying cause of many previously ineffective macro-prudential responses, suggesting that macroprudential monitoring based on SIFI-centered risk identification only aggravated a systemic crisis. This concern is further reflected in the limited definition of systemic risk that the ECB (2009) produced as 'one perspective is to describe it as the risk of experiencing a strong systemic event. Such an event adversely affects a number of systematically important intermediaries or markets'(p.134). In contrast, Patro et al. (2013) and Kritzman et al. (2011) asserted that to preclude systemic financial losses, surveillance based on asset pricing has the underlying benefit of being more predictive. Abdymomunov (2013) produced a more detailed definition of systemic risk, suggesting that 'in general, systemic risk is perceived as the risk of a negative shock, severely affecting the entire financial system and the real economy. This shock can have different causes and triggers, such as a macro-economic shock, a shock caused by the failure of an individual market participant that effects the entire financial system due to tight interconnections in the system, or a shock caused by information disruption in financial markets'(p. 455). In addition, Patro et al. (2013) held that ensuing liquidity and credit risks trigger events that are strong enough to cause a severe decline in the financial system. In recent decades, there are greater concerns about such events spreading across all sectors and the resources transferring from productive segment to financial segment, heightening the probability of recurring financial instability due to massive financialisation (Grilli et al., 2014). As an aside, Glasserman and Young (2015); Papanikolaou and Wolff (2014) and Battiston et al. (2012) suggested that an unprecedented level of newly emerged financial products, largely ambiguous in terms of the risks they bring into complex formations are, drawing investors' attention. In effect, unequivocally creating an intricate web of complex networks across borders exposes every participant to unseen risks.

In an attempt to address all the tenets of systemic risk, there has been much discourse about the gauges of capital shortfall in SIFIs. Some of the popular measures are CoVar, systemic expected shortfall (SES), marginal equity shortfall (MES), exposure CoVar, SRISK, granger causality and other linear and non-linear methods. However, these methods are not without their limitations and, as such, have spurred discourse about their ability to address capital shortfall and stress tests based on regulatory data (Silva et al., 2017). Being a popular measure of capital shortfall, Adrian and Brunnermeier (2011) proposed that CoVar is not able to properly identify temporal volatility that institutions inherit, or cannot capture the size and leverage of the institutions. Similarly, Adrian and Brunnermeier (2011) proposed that exposure CoVar is a tractable MES with some reverse conditioning. Billio et al. (2010) outlined five different measures of systemic risk, including non-linear estimations of volatility and linear estimations for causality. While granger causality is the commonly applied method for testing systemic networks that can affect a system-wide capital shortfall, Acharya et al. (2012) suggested that it can only be partially correct for measuring shocks or shortfalls. Given the potential for several institutions to simultaneously granger cause each other and that it is nearly impossible to consider all possible institutions in the equation presents a fundamental limitation of granger causality for measuring institutional risks. Further, this argument implies that individual institutions, as a function of systemic vulnerability, are erroneous; by extension, exposue CoVar or MES lose credibility. Acharya et al. (2012) proposed that structural methods such as SES condition the capital shortfall of an individual institution. Brownlees and Engle (2016) contended that structural methods rely on realised observations and the efficacy of these methods cannot be extended to ex-ante measures, demanded by regulators. The authors suggested their proposed SRISK measure has better predictive power and support the methods proposed by Acharya et al. (2012).

Since GFC, systemic risk estimation techniques examining inter-temporal linkages between markets and institutions have taken on greater urgency. Diebold and Yilmaz (2009) also quantified return and volatility spillovers in the intertwined markets, which was adopted quickly in the literature. Because the method was sensitive to reordering, Diebold and Yilmaz (2009) resorted to randomly chosen permutations. Extending from Diebold and Yilmaz's (2009) findings, Klößner and Wagner (2014) proposed a fast algorithm allowing timely calculations over all renumerations of spillover estimations, which was built on a divide-and-conquer strategy. In response, Diebold and Yilmaz (2012) adapted the original algorithm by switching the underlying framework from Cholesky factor orthogonalisation to generalised variance decomposition (GVD), turning the forecast error variance decomposition invariant to ordering. Diebold and Yılmaz (2014) further extended the use of DY spillover measures by adapting this method for examining network connectedness. Diebold and Yılmaz (2014) proposed that calibrating GVD underpins the modern notwork theories adapted from Acharya et al. (2012). The only other identification approach closer to GVD approach is the method proposed by Bonaldi et al. (2015), where the connectedness matrix of a weighted directed network is represented by first order VAR coefficients. Recently,Baruník and Křehlík (2018) proposed a spectral frequency based connectedness measure, in which the heterogeneity in the frequencies are attributable to calm and crisis cycle components generating shocks at different strengths.

Another strand of the literature focuses on a ‘source-specific approach’, which identifies risks cast out of specific sources (He and Krishnamurthy, 2014b; Jobst, 2014; Chang, 2016; Cont and Schaanning, 2017). While this strand of the literature has provided a host of complex macro-prudential approaches to regulators to manage a crisis, it is essential to understand that its integration with ‘global approaches’ are more statistical in nature. The configuration in a ‘global approach’ detects the changing dynamics in risk transmission, which emphasizes on flexible regulatory measures at different times proposes tools such as SRISK, CoVAR (Acharya et al., 2012; Brownlees and Engle, 2016; Brownlees et al., 2017). What stands out here is the risk of misconfiguring identification techniques by focusing on banking-led crises only. Approaches identifying systemic risk dynamics in a more holistic associated network with an underlying order-invariant generalised structure allows us to integrate statistical measures with flexible policy suggestions, a process involving domestic and international financial markets, instruments and institutions (Acemoglu et al., 2015; Diebold and Yilmaz, 2015; Diebold et al., 2017a; Dungey and Gajurel, 2015).

Given the benefits of taking a holistic network approach, in chapter 4, we investigate risks emanating from international equity markets with novel approaches such as SVD and MHD (Dungey et al., 2017a) against DY variance decomposition proposed by (Diebold and Yilmaz, 2012).

2.3 Securitisation

From a different perspective, Adrian and Shin (2009) defined systemic risk as an indication of regulatory failure to an extent that regulators do not aim to increase resilience of the entire system. This is particularly reflected in the growth of a country’s shadow banking. While securitisation may favourably contain idiosyncratic credit risks for an individual institution, it increases its leverage and desirably, strengthens its balance sheet. A snowballing of securitisation institutions builds in the fragility into of the system. According to Adrian and Shin (2009), the focus on micro-prudential regulation building has gained more attention in the extant literature, and concerns over macro-prudential regulations have long been avoided. Hence, there are more tools measuring risks endemic to individual institutions than there are risk matrices for the purpose of capturing potential risks turning epidemic. There is an escalation in the adoption of methods used in physics and epidemiology for identifying agents of chaos in the networks. However, in institution-specific studies, the relative size of the institutions and their exposures to potentially ‘standard’ risks are important elements of measuring criteria. However, Duffie (2013) stressed that standardisation of risks fuel herding behaviour, and the simultaneous adoption of common hedging or exit strategies by major institutions may lead to further market destabilization. In recent years, a pattern has emerged showing that an institution’s exposure to crisis is dynamic, and what follows is a general consensus for finding a right balance between macro and micro-prudential measures. Duffie (2013) suggested that the right balance can only be achieved by limiting stress testing to a small number of broad asset classes, which minimises Heisenberg uncertainty principle[1].

In the nexus between micro and macro prudential regulatory targets, what has come to dominate is the identification of what sources a crisis (Dungey* et al., 2005; Dungey and Renault, 2018). The demarcation of crisis from non-crisis periods shows the smooth transition from a micro-level crisis to a macro-level one (Dungey et al., 2015), in part driven by the strengthening of institutional securitisation, which spills risks over to security investors (Shin, 2009). Chen et al. (2017) argued that securitisation provides incentive to intermediaries to take higher risks when it is preceded by an expectation of significant risk reduction. Additionally, securitising agents incorporate higher quality loans in their securities, expecting a better rating and a reduction in regulatory capital buffer requirement while increasing risks on the balance sheet (Acharya et al., 2013). Earlier, Pennacchi (1988); Hughes et al. (1999); DeYoung et al. (2001) and Deng et al. (2007) reported that originators may transfer risks associated with underlying assets to security investors and gain geographic diversification. Routine diversification often leads to the scrambling of poor quality loans into transferred securities and the proliferation of low quality high risk assets in the market (Hakenes and Schnabel, 2010). This indicates a moral hazard and an influx in the number of risk takers that may also correspond to a crisis (Acharya et al., 2013). Berger and Bouwman (2013) concurred that such recklessness leads to a weakening of the originator's capital buffer, allowing them to draw down if conditions deteriorate. Moreover, Chen et al. (2017) provides evidence that securitising banks observe short-term risk reduction, while amplifying the probability of failure in the periods that follow.

This is analogous to compulsive gambling behaviour (AAC, 2020), as gambling presents the illusion of easy money but often leads to financial ruin. A compulsive gambler attempts to recover from a financial distress or to gain capital through gambling, which presents itself to be effortless. The losses that follow pushes the gambler further into a cycle out of which the gambler cannot step. Another type of gambler immerses themselves into repeated gambling only for the emotional impulses associated with placing bets. This type of gambler is similar to risk-taking investors; in all cases, what follows is complete financial ruin.

Many studies show that bank securitisation leads to higher systemic risks, while also increasing the bank's profitability and ensuring it has a buffer of liquidity for the bank (Battaglia et al., 2014; Georg, 2013; Bakoush et al., 2019a; Nadauld and Weisbach, 2012; Uhde and Michalak, 2010). However, as banking securitisation allows the banks to shed their own idiosyncratic risks into financial markets, and confirms a buffer of liquid assets coupled with higher profitability, a vicious cycle forms as banks' exposure to credit risk intensifies (Nijskens and Wagner, 2011; Adrian and Shin, 2008; ECB, 2008). According to Adrian and Shin (2008) banks naturally try to overextend their balance sheets and, as stated in the 'recourse hypothesis', this enables the banks to externalise their risks and amplify their credit risk-taking behaviour. In turn, the creation of contagion follows systemic risk building between banks and other sectors (Allen and Carletti, 2006; Allen and Gale, 2004). Moreover, banks hedge undiversifiable assets and subprime loans with buying of credit default swaps creating a channel of crisis across all sectors (Acharya and Yorulmazer, 2007; Elsinger et al., 2006a). This is was found be true following the GFC for European

[1]Increasing the precision in measuring one aspect of a system intensifies the uncertainty regarding the other aspect of the system.

banks (Uhde and Michalak, 2010), USA banks (Bedendo and Bruno, 2012) and Italian banks (Battaglia and Gallo, 2013), providing a theoretical foundation that securitisation increases profitability.

Taking a more granular approach, Acharya et al. (2013) showed that asset backed commercial paper (ABCP) conduits are the form of securitisation that leads to shadow banking runs. An estimated \$1.3 trillion worth of assets are securitised with ABCP conduits preceding the GFC. Commercial banks form and manage these conduits as special purpose vehicles with to reduce regulatory capital requirement. This externalises risks through diversification while providing recourse to money market funds and other investors into its own balance sheets. Integral to the financial intermediation process of depository institutions, conduits primarily convert the banks' holdings of medium and long-term assets to short-term assets and structure guarantees with the insurance sector to circumvent regulatory constraints. The shadow banking industry that transpires is evolving to retain risks while pursuing regulatory arbitrage by retaining rollover risks pertaining to maturity mismatch. Consequently, these risks pose significant threat to the sponsors assuming them. In effect, conduits are attributed with systemic risk involving commercial banks, insurance institutions and equity market components. Evidently, in the unfolding of GFC, the extent to which commercial banks lost stock values is attributable to conduit exposure relative to loss of capital, more so for commercial banks involved in managing ABCP conduits. **Hence, a dampening of equities associated with depository institutions may indicate the degree of securitisation associated with risk retention in an economy.** In other words, this may indicate the deepening of shadow banking in the banking architecture.

2.4 Banks or equity markets ?

Notably, since the 2008 credit crisis several restrictions were imposed on banking securitisation, especially in advanced economies. The Association of Financial Markets in Europe reported significant reduction in the securitisation activities, especially for the USA and European banks (AFMEA, 2017). Evidently, this has impaired the capital and profitability of these banks as indicated by for International Settlements (2018). Mersch (2017) presented an account of attempts to revive risk transfer in capital markets, especially in USA and European economies, by providing a natural experiment to recover the changes in the risk transfer dynamics for these economies.

The 2008 crisis has also driven the central banks to enforce both measures to enhance liquidity provisions and interbank loan freezes for commercial banks against the fear of an untenable build up and unwinding of systemic risk within the interbank loan networks (Georg, 2013). Banks face a stochastic supply of deposits and interbank loans that link the banks, ensuring there is a continuing buffer of credit among them: this is the key to banking operations. While such static interbank loan networks form the money market, Haldane (2013) defined these interbank networks as robust, yet fragile, suggesting that interbank networks work on a knife's edge. Moreover, static networks work well for maintaining liquidity provisions by enhancing liquidity allocation and risk share between depository institutions, and they are an intrinsic part in the globalisation of banks (Battiston et al., 2012; Ladley, 2013; Gai and Kapadia, 2010). Conversely, interbank networks amplify shocks for all participants and face the insolvency of a strongly connected participant. *Acharya and*

Bisin (2014) defined such externality as a counterparty risk externality that fuels cascading defaults in banks, otherwise known as interbank contagion. Acharya and Bisin (2014) further suggests that a similar effect arises from one bank's holding numerous other banks' assets. *A correlation externality arises when common shocks rip through all parties in an interbank loan market due to the common holding of sub-prime assets sourced from defaulting banks.* Therefore, the fundamental banking activities are the source of untenable cycles of shock transmission, coupled with securitisation or shadow banking which provides a potential means for a downward spiral. However, the contribution of each participant disproportionately contributes to each trigger event and crisis propagation, and trying to gauge a generalised index of risk from these banks often leads to aberrations in outcomes.

Allen and Gale (1998) presented an interesting perspective to explain the crucial link between banks and equity markets, and policy direction geared towards impeding the growth of crisis in both sectors. A classical view sources crisis from 'mass hysteria', in which investors' panic due to an impending crisis is analogous to sunspots (Kindleberger, 1978). These extraneous 'sunspot' panics emit from speculations and lead to self-fulfilling scenarios. Fearing a bank's failure to fulfil its commitment leads to a synchronised withdrawal that drains the bank of liquidity, leading to bank failure and crisis precipitation. Alternatively, policies blunting the initial panic ensures there are few full withdrawals, resumes confidence in the bank's commitment and, dampens any further panic. Allen and Gale (1998) suggested that an 'optimal allocation' of risks is obtainable if bank runs are allowed within a controlled scenario. Banks shed risks into asset markets to stimulate cash flow. Facing a downturn, banks liquidate capital market assets that, in turn, forces asset prices down. Hence, if intervention strategies are simply geared towards preventing a capital market collapse, a Pareto improvement is observed in the banking sector, which satisfies the self-fulfilling prophecy. In this way, banking interventions can be a tool used to protect a few large banks from a cascade, and capital market interventions may protect the economy. **In this regard, examining banking sectors for systemic risk-led crisis generation is investigating the wrong facet of the problematic.**

This dichotomy is reflected in the tenet of studies identifying sources of crisis. The ubiquity of systemic stress across multiple sectors in the unfolding of a crisis makes it arduous to look for a unique sector reflecting the dynamics of crisis. Intuitively analysing the systemic banking connections identified by earlier studies has led to discourse in capturing the dynamics of boom-bust cycles. Evidently, there is strong interconnection between systemic risk propagation in banking and in stock markets. Myers (1977) asserted that fearing run-ons, banks naturally siphon off large, collaterised debts, which effectively devalues all common equities built into similarly constructed debt portfolios. A systemic decline in equity indices indicates widespread systemic banking declines. While investigating unprecedented losses in the long/short equity hedge funds during the USA quantitative meltdown of 2007 followed by coordinated deleveraging of equity market-neutral portfolios, Khandani and Lo (2011) surprisingly found indications of macro stress building and shifting patterns in equity price expectations. **Apparently, signs of distress across many sectors are more effectively gauged using equity market systemic risk analyses.**

An increasing number of commentators give credence to this notion. Hanson et al. (2011) evinced that declines in equity indices are directly connected to forced liquidation of similarly constructed debt portfolios in the banking sectors. A resulting fire sale triggers a twin crisis, which then merges micro-level downturns into a complete economic downturn. Diamond and Rajan (2011); Shleifer and Vishny (2010) and Stein (2010) found unerringly positive similarities between equity market fire sales and bank credit crunches. In effect, classic bank run-on is indistinguishable from a stock market crash (Gorton and Metrick, 2012; Covitz et al., 2009). Further, the rapid accumulation of credit bubbles spurs macro-economic vulnerabilities and systemic connections in equity markets, which provides a perfect platform for modelling crisis (Dungey et al., 2020; Krishnamurthy and Muir, 2017b; Moreira and Savov, 2014; Adrian and Shin, 2009; Reinhart and Rogoff, 2009).

2.5 Feedback loops

Crisis manifests when common shocks, which span across multiple sectors become mutually reinforcing. Such crises transpire from one or more feedback loops involving financial market and real sector activities. Davis et al. (2010) asserted that financial frictions are responsible for adverse feedback loop formation. Unprecedented shock leads to devaluation in prices for the assets being held in financial institutions and markets, resulting in an increase in credit risk that is also reflected in the heightening defaults in the real sector. A first feedback loop is generated when the financial frictions in the real sector affects the market for long-term capital financing. Under such circumstances, the creditors' loss of confidence affects the loan market that the banks manage from within. This pushes the interbank rates up because the diminishing access to newer funds disrupts the intermediation managed by the depository and financial entities. Given the banks also maintain small capital cushion, the financial friction in the banking sector leaves them with no alternative but to cut short-term lending to the real sector. By having access to lower working capital real sector and resorting to shrinkage, this forms a second feedback loop concerning both the financial and banking sector. The overall economy is mired in deep recession when both feedback loops spiral out of control.

Stein (2010) and Hanson et al. (2011) explained this connection with trenching. Most often, institutional investors rely on short term borrowings for buying trenches of securities. Such trenches of assets are produced by entities such as 'structured investment vehicles' that are often affiliated with banks and depository institutions. Such holdings are used to finance overnight collaterized borrowings in the repo market, in form of 'repurchase agreement', that in turn are used by banks for 'deleveraging', reducing cost of raising capital, leading to the formation of a 'shadow banking system'. According to Stein (2010); Hanson et al. (2011) this 'shadow banking system' is to blame for systemic risks in banks to contribute in developing systemic risks for equities and vice versa. More recently Brunnermeier et al. (2016) provided evidence that in trenching common equities for two banks are build into collaterized debt obligations that are traded in repo markets. In the event of an institutional investors failure to roll over financing, leading to essential fire sales drops the market price for the common equity and in turn reduces the value of portfolios maintained by a different bank located in different countries. **Here, a contagion formed within the banks contribute to systemic risk building in equity markets across borders.**

Farhi and Tirole (2017) provided an interesting insight into how these feedback loops form involving the banking sector and public debt sectors, which they termed a 'doom loop'. These authors asserted that this loop is important. They claim it will appeal to international creditors who consider sovereign debts and the renationalisation of public debts when facing a crisis, while also calling for better macro-prudential regulations concerning bailout precepts. In effect, an adverse economic shock has direct and indirect consequences for both the fiscal and real sectors. The direct effect involves diminishing fiscal returns concerning sovereign bonds, which fuel further economic downturn. The indirect consequence is reflected in bank balance sheets, because as the price of public debt descends, the decreasing total value for the bank leads to bailouts. Regulators finance these bailouts by issuing additional public debts, which induces additional stocks for sovereign debts that dampens sovereign bond prices. Consequently, a 'doom loop' emerges that reinforces the nexus between sovereign debt and bank balance sheets driven by the extent of 'home bias'. **This issue will be explored in the context of equities, both numerically and visually, in chapter 3.**

Stress sourced from banking activities while presenting public debt as a safe haven is widely reported in the extant literature (Acemoglu et al., 2015). For banks with a higher degree of intermediation, Acharya and Steffen (2015) proposed 'risk shifting' between these institutions and periphery debts across multiple countries. Dungey et al. (2019) provided evidence of financial fragility within an international setting that complement the self-fulfilling feedback loops across the periphery sectors. Thus, a primary challenge going forward is gauging public sector debt held by the banks, while bearing in mind the blurring of direct bank involvement with derivatives and trenching. Again, the disproportionate means through which to channel risks into the real sector has induced spurious reasoning concerning generalised shrinkage (Dungey et al., 2019).

Brunnermeier et al. (2016) supported the diabolic-doom feedback loop notion by proposing some solutions to ameliorate the sectors that induce feedback loops. First, banks must restrict exposure to stricken public sector debts and increase exposure to equities in pooled assets. Second, banks should only hold senior public debts, or preferably, the senior tranches of well-diversified international sovereign portfolios, such as ESbies. Insofar as the diabolic loop is contained then, intuitively, the junior trenches will be risk free. In the context of mutually reinforcing feedback loops, this shifts sovereign risk away from the banks to junior bonds and eliminates the need for bailouts. However, while such targeting trenching may diffuse contagion, they may also invoke systemic risks in securities.

2.6 Financial contagion

In recent studies concerning systemic risk, it is generally accepted that systemic risk attributed to financial institutions does not lead to an imminent crisis (Dungey et al., 2020). It is the trigger of contagion-led systemic crisis that we consider financial crisis. However, the extant literature draws on only one of the two key concepts when discussing crisis, which has formed two separate tenets. More alarmingly, the extent literature seems to focus on one of the tenets to draw conclusions regarding crisis, which reduces the plausibility of its crisis theories (Duffie, 2013; Romer and Romer, 2015; Darolles and Gourieroux, 2015). In effect, implausible gauges remove important stages of crisis, resulting in spurious policy remarks. Therefore, the key to addressing crises is identifying these two inherent stages and gauging the interplay that essentially forms a feedback loop.

Evidence of transmission between markets during crises and the changing size and direction of spillovers poses challenges for diversification and regulatory policy. A substantial literature addresses contagion and volatility spillovers as a mechanism of transmission, particularly in assessing changes in the contemporaneous interdependence among variables (Collins and Biekpe, 2003; Forbes and Rigobon, 2002). While Collins and Biekpe (2003) defined contagion as reversals to net capital flow to an economy, Forbes and Rigobon (2002) argued that the correlation between market returns is largely due to common factors, and hence represents interdependence rather than contagion. A variety of identification approaches to separate contagion, interdependence and volatility spillovers exist (Diebold and Yılmaz, 2015; Acemoglu et al., 2015; Bekaert and Harvey, 1995; Bekaert et al., 2013; Chambet and Gibson, 2008; Eiling and Gerard, 2011; Brooks and Del Negro, 2005; Pukthuanthong and Roll, 2009).

Common shocks spilling out of origin and spanning across multiple sectors may build into a crisis. However, systemic risk found within multiple sectors does not lead to a cascade if there is no contagion and if liquidity is well diversified for both markets and systematically important financial institutions (Allen and Carletti, 2006). A pronounced rise in systemic risk may lead to credit risk transfer between sectors, forming contagion, which further exacerbates risk transmission as a conduit (Allen and Carletti, 2010; Billio et al., 2012; Bonaldi et al., 2015; Dungey et al., 2017b; Farhi and Tirole, 2017). This may lead to a large-scale crisis. Thus, systemic risk and contagion may be closely associated with crisis formation. Khandani and Lo (2011) supported this argument by proposing the 'unwinding hypothesis', which explains systemic risk building in the equity markets with feedback loops forming elsewhere. **A key issue in the current context is concentrating out the tipping point in shocks that manifest into crisis, and we discuss and visualise this issue in Chapter 3.**

Earlier, Allen and Carletti (2006) established the stages implicit in crisis building within the context of the banking and insurance sectors. Credit risk transfer between these two sectors is beneficial to welfare if there is uniform demand for liquidity, but is detrimental to idiosyncratic risk. For crisis to manifest in terms of interdependence, the precept for both the banking and insurance sectors is to manage long and short-term assets across different contingencies, despite operating differently. We consider two contingencies, and compare both sectors when they have a common demand for liquidity against when they do not have a common demand for liquidity. In autarky, the sectors with no interplay subjects the insurance sector to systemic risk, but the banking sector less so. Under such circumstances, if returns on risk-free long-term assets are less than the returns on risky loans, the banks will immerse themselves into intermediation and service risky loans using short-term assets. Facing aggregate risk, insurance institutions service partial insurance against premiums from these short-term assets. If the insurance sector fails to pay off its losses, then bankruptcy will follow. However, these risks are benign and do not lead to a cascade.

If the banks have a common demand for liquidity but face no idiosyncratic risk, then credit risk transfer is beneficial for the banks' welfare. Further, it allows banks to optimise their profit without factoring in contagion, and to invest in risky loans while holding short-term assets (i.e., autarky). In contrast, the insurance sector preferably holds long-term assets to enable them to transfer risk and liquidate only when their clients incur a loss. The prices received from holding these long-term assets are low and facing aggregate risk insurance institutions may go bankrupt by failing to pay all insurers. This does not lead to crisis building (Allen and Carletti, 2006).

If banks have a common demand for liquidity but face idiosyncratic liquidity risk, then credit risk transfer may not remain beneficial. By having depositors who withdraw at different times, banks can hedge this risk by holding onto long-term assets and trading them in the loan market. In contrast, insurance institutions face no aggregate liquidity risk and invest in the premiums from short-terms assets unless their clients incur losses. In any case, the insurance sector may feel the tremor when clients feel crisis simultaneously and insurance companies may still go bankrupt (Allen and Carletti, 2006).

In both these cases, a crisis does not manifest despite the sectors reaching crisis points. At this point, inducing additional credit risk may precede larger repercussions for welfare. Fuelled by additional credit risk, insurance institutions liquidate their holding of long-term assets, which slashes underlying prices. This, in turn, amplifies systemic risk in the interbank market. Contagion acts as conduit for systemic crises across the insurance and banking sectors and then back to the insurance sector, leading to a Pareto reduction in welfare. In the context of incomplete markets and plunging asset prices, contagion across many illiquid markets leads to a worsening spiral involving many financial institutions (Allen and Carletti, 2006).

Piccotti (2017) argued that there exists a symbiotic relationship between contagion and systemic risk. Financial contagion defines the spread of market disturbances and poses a potential threat for economies by attempting to integrate with international financial system. This also explains the extent to which a local crisis may propagate across neighbours and warrants investigation beyond real economic factors. Conversely, systemic risk suggests the risks that exist within a system of nodes comes from the strength of these nodes. Endogenous credit and capital constraints turn non-systemic risks into systemic risk as crisis propels through different markets followed by a reinforcing cycle. Additionally, crisis propagation brings about temporal changes to aggregate elasticity of temporal substitution affecting asset prices in different markets (Holmstrom and Tirole, 1996, 1997; Kiyotaki and Moore, 1997; Longstaff and Wang, 2012; Elliott et al., 2014; Shenoy and Williams, 2017). Hence, financial contagion increases all costs, as the marginal utility of consumption is negatively affected in the short-term for long-term investors. Consequently, investors short term holding time preference attributes a higher price to contagion (Van Binsbergen et al., 2012, 2013; Belo et al., 2015). Drawing a distinction, Piccotti (2017) suggested that financial contagion may positively affect the marginal utility of consumption corresponding to assets with a longer holding period, subsequently decreasing contagion costs while generating higher returns for risk-takers. Fernández-Rodríguez et al. (2016) define interconnectedness as a bridge between two crucial visions, 'pure contagion' and 'shock spillover'. **We are provided with an ideal natural experiment to investigate the degree to which investors' aggregate risk-taking makes a given market more contagious. In other words, we aim to identify if high-risk spillovers are positively associated**

with high aggregate risk tolerance. In addition, we account for similitude between homogeneous information transmission corresponding to crisis transmission. Such similitude may indicate the role of investors' collective risk tolerance in building a crisis.

There is a substantial effect on the economic fundamentals when faced with domestic contagion, in which individual domestic portfolios are vulnerable to risks stemming from domestic markets. This may lead to 'home bias', a stylised term manifesting itself into the 'wake-up call' hypothesis, in which investors parse information coming from other countries' markets as representing vulnerability when their own market is mired in deep recession (Goldstein, 1998a; Kocaarslan et al., 2017). Trade and bank linkages are not necessary conditions under this hypothesis, while market exposure to each other depends on the strength of their own institutional and economic fundamentals. 'Spillover' and 'contagion' are considered to address excessive co-movements of asset returns preceding a crisis due to unidentifiable sources of shocks. Earlier studies such as Lin et al. (1994); Hamao et al. (1990) could not link fundamentals causing such shocks.

A plethora of studies have examined fundamental based contagion in the last decade. Fundamental based contagion refers to risks that may lie within trade and financial linkages between different economies (Longin and Solnik, 1995; Ang and Bekaert, 1999; Forbes and Rigobon, 2002; Dooley and Hutchison, 2009; Chiang et al., 2017). Goldstein (1998b) proposed a 'wake-up call' hypothesis that outlines a markets vulnerability to crisis speculation. Bekaert et al. (2013) provided evidence of 'wake-up calls' causing contagion in the post-GFC period. Intuitively, it is easier to classify market susceptibility by clustering the markets by commonality in fundamentals. **However, we believe the other type of contagion based on investor behaviour bears equal importance in identifying crisis transmission channels.**

Financial contagion studies have taken on greater urgency since the Asian financial crisis of 1997, with little emphasis on investors' risk tolerance as an important factor. In an attempt to catalogue financial contagion papers, Seth and Panda (2018) reviewed 151 studies, only five of which discussed investor-based contagion as a key state variable despite investor overreaction being central to crisis transmission. Chudik and Fratzscher (2011) pointed out that the degree of investors risk tolerance coupled with the tightening of liquidity as a conditional element in crisis, causes differing levels of transmission in both emerging and developed markets. Mondria and Quintana-Domeque (2013) provided empirical evidence that managers' increasing attention to crisis countries heighten crisis transmission. Dungey and Gajurel (2015) rationalised that herding behaviour fraught with asymmetric information generates contagion from the USA to emerging markets. In contrast, Shen et al. (2015) found that Chinese markets receive shocks during crisis, more so from macroeconomic channels in the European markets than from investor based contagion.

Investor-based contagion is primarily caused by dynamics in investors' risk perceptions and risk appetite, which determines how investors re-allocate investments internationally (Masson, 1998; Dornbusch et al., 2000; Forbes and Rigobon, 2002). On the one hand, dampening risk tolerance may lead to frequent re-balancing of investor portfolios (Kodres and Pritsker, 2002; Fleming et al., 1998). Conversely, magnification in risk tolerance drives investments towards riskier asset allocation

(Kocaarslan et al., 2017), which simultaneously pushes the prices of risky assets upward. Such contagion resurges due to the restructuring of portfolios by investors, and less so due to market swings (Kumar and Persaud, 2002).

Bekaert et al. (2013) and Masson (1998) investigated contagion further by defining its classes under different settings in the economic fundamentals. In a multi-factor model, a ‘domestic contagion’ is when the integration of asset returns moves in lockstep with other observable domestic factors. This, returns confirm the notion of ‘residual contagion’, similar to outliers when the returns are not associated with the domestic factors. Contemporaneous shocks may ensue due to some common causes, such as intervention policies to improve markets following a downturn that some bigger markets might take, affecting the dynamics in some smaller markets. This is termed a ‘monsoonal effect’. Crisis that spreads outside the border of one country into another while having similar economic fundamentals is termed ‘spillover’(Masson, 1998). The modest difference between these two definitions has been blurred in the extant literature (Seth and Panda, 2018). Insofar as the purest form of ‘contagion’ remains, the underlying sources of shocks are not tractable in economic fundamentals and financial markets are driven by ‘sunspots’. In effect, one possible cause of the limitations of these definitions is the extent to which risk appetite exceeds that of economic fundamentals to reach an equilibrium in which crowded investments move in lockstep and, consequently, information spillover ensues. In summary, the (Dungey et al., 2019) discourse in theorising contagion is reflected in how contagion identification techniques are shaped by researchers, which drive them away from the definition of ‘contagion’. **Both ‘systemic risk’ and ‘investor sentiment’ have branched out of ‘contagion’ studies (see Table 2.1).** Such sparsity has narrowed the focus of research into contagion to examine its effects but not its causes, highlighting a knowledge gap that requires exploration to identify causes of systemic crisis.

A common concern is volatility diffusion into high and low states during turbulent times, which directly affects individual market’s responsiveness to other markets. Flavin et al. (2008) termed this phenomenon ‘shift contagion’. As an aside to identifying crisis patterns and short circuiting its pathway, the literature comprises interesting research into equity and foreign exchange interconnection, which enriches our understanding of other ways to form diabolical loops outside a country’s periphery (Bekaert and Hodrick, 1992; Tai, 2007; Anderson et al., 2015; Yang et al., 2016). As a similar contagion arises, foreign investors lose expected returns on investment, while domestic investors find it difficult to diversify their investments because they lose some degree of purchasing power. This scenario may, in turn sprout pure contagion, exacerbating the situation. Goldstein (1998a) examined investors’ re-evaluation of their losses in all other peripheries that face a crisis in one country. Investors explaining information regarding common risk factors trigger contagion in different ways across other markets, even when the banks have no real exposure to each other. For example, in the aftermath of the Asian financial crisis, it was observed that rational speculators were exposed to asymmetric information that propagated crisis through ‘pure contagion’. Among others, Calomiris et al. (2012) found that, in addition to selling pressure, credit supply and demand shocks negatively affect individual stocks during crisis but remain undetected in the preceding periods.

Recently, Cont and Schaanning (2017) held that fire sales and contagion through bank balance sheets are more damaging than other sources of contagion. Unprecedented shocks significantly dampen asset values, particularly when portfolios holding such assets are constrained in terms of leverage or capital. Crisis precipitates as loss of asset values conditional on constraints reach a tipping point. Adrian and Shin (2010) indicated that fire-sales externalise the risks of value loss across asset categories and financial institutions through a 'loss contagion' channel. The findings are in line with the research of Cont and Wagalath (2016); Caccioli et al. (2014); Shleifer and Vishny (2011) and Kyle and Xiong (2001). Conversely, direct pairs between banks or financial institutions due to common asset holdings form a price-mediated contagion channel that may also trigger contagion in the absence of direct links between institutions. Hence, ameliorating the exposure to common asset holdings, or a price intervention, may successfully attenuate fire sale spillovers. Regulators may prefer to introduce deposit and debt guarantees that insulate equity markets to some extent while reducing exposures.

Farmer and Foley (2009) provided evidence of crisis transmitting from hedge fund investments to stock prices with 'agent-based model' simulations involving agents (i.e., 'noise traders' making random trades), hedge funds (that hold underpriced stocks or cash), investors (who invest specifically in hedge funds) and banks (that lend money to hedge funds). Naturally, hedge funds push stock prices back to their fundamental values, dampening the volatility of stocks. These hedge funds are leveraged, and banks often cap leverage for risk minimisation. Hence, a sudden drop in stock prices affects the value of the hedge fund, and the fund sells stocks to offset plummeting wealth. This, in turn, triggers a fire sale, contributing to crisis amplification. Similar to the hypothesis proposed by Farmer and Foley (2009), Lo (2011) examined 'crowded trade' phenomenon for an entire class of hedge funds triggering crisis.

Seth and Panda (2018) produced a taxonomy of contagion that identified from 151 articles published between 1990 and 2015, of which 124 are published in peer reviewed journals. The review also includes 27 working papers available from organisations such as the International Monetary Fund and the National Bureau of Economic Research.

The combination of key terms these studies provided to locate their research differ significantly: 101 papers include contagion only, 20 papers include contagion and integration, 19 papers include contagion and spillover, seven papers include contagion or interdependence and four papers include contagion, spillover and integration. This further reinforces our argument that the extant literature narrows the focus to 'shift contagion' studies only, dismissing the patterns or causes that may lead to early warning signs of crisis. We can observe few perspectives in which contagion is different from interdependence. Naturally, the terms coincide given the almost indistinguishable differences in definitions.

Given that most (57 per cent) of the studies identified in Seth and Panda's (2018) review focused on stocks only, this presents a major opportunity to investigate and visualise crisis transmission pathways or contagion patterns emanating from global stocks. Among others, 6 per cent of the papers covered stock and bond, 5 per cent investigated stock and foreign exchange, 5 per cent covered only bond, 5 per cent covered foreign exchange and 3 per cent covered other economic fundamentals. All these papers examine contagion under different settings, but this does not necessarily mean the authors suggest ways to short circuit a recurring crisis. Moreover, while

93 per cent of these papers used a sampling period of between one and 15 years, only 1 per cent of the papers included a sample size of 25 to 30 years (Seth and Panda, 2018).

Seth and Panda (2018) also summarised the proportion of the contagion literature coming out of specific countries. Researchers from the US, Australia, Greece, the UK and Germany contributed to 12, 11, 7, 7 and 6 per cent, respectively, of the contagion literature. Among others researchers, those from Brazil, France, Italy, the Netherlands, Tunisia, Bangladesh, India and Korea contributed between 2 and 3 per cent. The maximum number of papers published in any one year increased from 11 papers in 2010 to an astounding 24 papers in the most recent year.

As mentioned previously, the number of studies centred on contagion has increased significantly. *However, few define contagion and interdependence separately, and even fewer attempt to distinguish the terms empirically.* This is partly due to the lack of a tractable framework that does not require nesting of multiple methods. The hypothesis suggesting 'interdependence' has a lesser negative connotation than does 'contagion' or 'systemic risk' is less conspicuous in empirical techniques. However, to suppose that we can consider one without the other simply draws us further away from our objective: discovering ways to fend off a crisis. *The seminal work from Forbes and Rigobon (2002) distinguished 'interdependence' and 'contagion'. Further, these authors proposed a widely accepted definition, suggesting that in the case of two markets, countries or institutions, the explicit showing of co-movements during calm periods will not be considered contagious despite amplifying co-movements in crisis involving both indices.* However, it is contagion when such co-movements are triggered, which causes widespread crisis only. Key to this insight is the simultaneous volatility increases that underpin the cross-correlation increases between factors. The bias is a result of heteroscedasticity and, if untreated, gives spurious identification. Hence, in all turbulence, the gyrations in the cross-correlation index is erroneously dubbed as contagion. *Using a different framework Darolles and Gourieroux (2015) and Duffie et al. (2009) also distinguished frailty from contagion. In fact, this explains why contagion identification abounds in the recent literature.* Earlier, the implications of such spurious identification of contagion was highlighted in Billio and Pelizzon (2003).

Recently, Dungey and Renault (2018) complemented the seminal work of Forbes and Rigobon (2002) by identifying important gaps in that study. Dungey and Renault (2018) suggested that volatility of common factors in both 'source' or 'target' often contributes to the transpiring of simultaneous contemporary jumps in volatility. In the absence of a widespread crisis, such jumps may not pertain to contagion. Consequently, using traditional methods, the gyrations in the market often obscure the process that measures contagion. In Chapter 4, we consider the nexus between these two issues by taking a simple but effective approach to distinguish between contagious markets.

2.7 Financial networks

The extent to which the casting off of risks borne out of pre-existing conditions in the financial system may induce contagion lies within the structure of financial networks. This is a well-studied phenomenon (Cabrales et al., 2017; Acemoglu et al., 2015; Elliott et al., 2014; Allen et al., 2012; Acemoglu et al., 2012; Haldane, 2009;

Freixas et al., 2000; Allen and Gale, 2000). Drawing on previous empirical research, financial networks measure the web of exposures within interconnected institutions at any given point in time; thus, financial networks are implicitly static (Giraitis et al., 2016). A primary challenge going forward is to identify the dynamics in the networks that respond to changes in market conditions, a process involving financial sectors and institutions holding common assets.

The dichotomy here stems from the conjecture that under certain conditions there exists a threshold inducing crisis from calm periods. A stylised fact suggests that a densely connected financial network is more resilient to shocks to any one counterparty in the network. The losses are diffused within the networks, precluding insolvency to participant banks and preventing any subsequent cascading defaults. Hence, excess liquidity should suffice in forestalling further defaults at the onset of a small crisis, but these effects would change dramatically if the gyrations in the negative shocks exceed certain threshold. Moreover, in line with the 'robust-yet-fragile' hypothesis, a complete network is conducive to a worsening spiral as financial distress spreads quickly across multiple institutions and sectors. An epidemic quickly turns pandemic. Recently, Dungey et al. (2018a) provided evidence that underlying systemic risks in a complete network may propagate from the financial sector to the real sector, affecting both employment and output. This posits that the most systematically threatening outcome consists of swings of negative shocks over a sustainable threshold. It also leads to a systematic increase in risk-taking across multiple sectors, leaving them wide open to heightened negative shocks. *Indeed, Elliott et al. (2014), using a model in bankruptcy cost, defined 'chain reaction' as the corresponding impairment of all institutions' value that owns a common share underlying an affected institution.*

In contrast, sparsely connected 'ring' networks[2] are less susceptible to an immediate crisis. If there is a large institution in the middle of network, one of its constituents, the senior liabilities absorb major shocks and as such bring distress to senior creditors, and while minimizing losses for all other creditors (Cabrales et al., 2017). Further, incomplete networks often set the stage for contagion, while complete networks help attenuate it (Dungey et al., 2018b). A complete review of the literature indicates that injecting the most systemically important counterparties with liquidity in times of crisis helps minimise the spread of contagion (Dungey and Gajurel, 2015). Any reliable conclusion must include that a successful intervention relies on information regarding the shock sizes, frequency and other characteristics (Dungey et al., 2019). Imposing restrictions on exposure between financial institutions, fearing effects from expected small shocks, is counterproductive if faced with a relatively big shock. Such interventions also raise concerns regarding moral hazards.

While the extant literature reports that a pre-condition is to set a fixed network structure, level of vulnerability due to contagion is often inherent within the network structure (Giraitis et al., 2016; Allen and Babus, 2009). On the one hand, a strongly connected network is also the more resilient to contagion, see Allen and Gale (2000). Conversely, dynamics in the complexity of the network and changing node concentrations indicate frailty (Gai et al., 2011). **In summary, a strongly connected network in which the nodes are more dispersed rather than concentrated is less vulnerable to contagion. This issue will be discussed**

[2]A ring network is when liabilities of all other institutions are concentrated into one counterparty.

in chapters 3 and 4 of this thesis.

2.8 Risk perception & information transmission

2.8.1 Information transmission

Although the systemic crisis and contagion literature has placed greater urgency on its findings since the GFC, it appears there is little concern over corresponding news transmission affecting the dynamics of investor risk behaviour. This in turn, leads to risk spillovers and contagion. In the seminal work of Dooley and Hutchison (2009), the authors concentrated out 15 types of news, including both economic and financial news corresponding to the 2007–2008 GFC emanating from the USA market. The authors estimated that at least 14 emerging economies were directly affected by news transmission, even before these economies were affected by the crisis itself. What follows was a phenomenal decoupling of emerging markets from the developed markets over a period of 14 months until the markets started to recouple in May 2008.

This decoupling is evident in the 'event studies' conducted by Dooley and Hutchison (2009). These authors showed a remarkable response by the emerging markets that precluded these markets from having high sovereign defaults or phenomenal equity collapses. Indeed, these markets could not keep themselves insulated for a long time; as recoupling emerged, new innovations from the USA and Europe hit the emerging markets. **Our hypothesis (see Chapter 5) proposes that news transmission predates crisis transmission, providing regulators with a potential window to decouple from sources.** This may also provide a means to diffuse the effect of a pandemic for the home country.

The dynamics in information channels largely drives portfolio rebalancing. Homogeneous information affects investors' risk perceptions, which are induced from cross-market hedging (Fleming et al., 1998) and increasing interconnectedness between markets. However, Kodres and Pritsker (2002) argued that risk transmission depends highly on information asymmetry coupled with shared macro-economic risks. In chapter 5, we split our markets based on both shared macro-economic history and macro-economic risks. We order the markets to separate out emerging markets in which information asymmetry may dictate.

Information transmission stimulates active hedging by invoking frequent asset reallocation by investors, which heightens in crisis periods compared to calm periods. This, in turn, increases interdependence (Lehkonen and Heimonen, 2014). Lehkonen and Heimonen (2014) argued that for active investors (e.g., large investment banks) are mostly driven by shorter-term dynamics, whereas passive investors (e.g., individuals, insurance companies and commercial banks) are driven by longer-term dynamics with a higher risk tolerance. Therefore, during stable periods interconnection remains neutral to an extent that hedging in the markets are driven by information symmetry. Conversely, during crisis periods, risk-takers and risk-averse investors alike participate in active hedging in fear of diminishing portfolio values (Kodres and Pritsker, 2002; Kocaarslan et al., 2017). Aggressive portfolio rebalancing on top of perceived increases in information asymmetry elevate linkages in global networks.

A crucial tenet of econometric research endeavours to model information transmission and relies heavily on extrapolation, to produce these studies' expectation variables (Fazzari, 1985; Wallis, 1980; Neary and Stiglitz, 1979; McCallum, 1976; Lachmann, 1943; Harrod, 1939; Hicks, 1936). Muth (1961) coined the term 'rational expectation' by extending the former, proposing that agents contemplate associations among variables while forming expectation. This prepares new investigations to measure systematic biases or effects of information inefficiency in studies on, for example, market speculations and dynamic equilibrium problems. The principles of 'rational expectation' lay out a state in which the economic system provides no allowance for information emitting from the markets. Second, the fervent application of 'rational expectation' does not require changes in models corresponding to changes in economic structure. The last principle states that, economic systems do not rely on 'public predictions'. Fazzari (1985) argued, 'rational expectation' and what follows relegates the vestiges of Keynesian and post-Keynesian theories to special cases of equilibrium models. Hence, despite the proponents of 'rational expectation' arguing that optimal conditions bring stability to the markets, the proponents of Keynesian theory contend that 'rational expectation' rather has a rather destabilising effect on the market economy(Fazzari, 1985). At the height of this debate, both contending principles were drawn from the locus of control indicated in the famous critique by Lucas et al. (1976), who held that empirical models cannot lead to successful policy implementation. Additionally, any policy implementation fervently alters the underlying econometric model. In other words, Lucas et al. (1976) advocated that only counterfactual analysis matters and predicting the consequences beforehand with forecasting models based on expectation is rationally beyond the capacity of econometric techniques.

Against this background, the 'efficient market hypothesis' was proposed by Samuelson (1965) who suggested that better price anticipation invokes their random fluctuations. Moreover, Malkiel and Fama (1970) reported that simulation outcomes conditional upon multiple information sets showed that 'prices reflect underlying information'(p.383). In other words, the more efficiently that information transmits within a market, the more unpredictable the market becomes. This school of thought conceives that investors seize all available information in the market, eliminating any arbitrage opportunity. This then becomes incorporated in the price of assets, which revises the price altogether in a 'frictionless' market. While this notion of having a 'frictionless' market is conducive to economic predictions, the required state of the economy is rather hypothetical (Getmansky et al., 2004).

The information channel is imperative to separate out the crisis propagation pathway, similar to risk premiums corresponding to investors' expectations about the market and overreactions to crisis-related information (Malmendier and Nagel, 2011; Barberis et al., 2015). Thus, financial crisis is better identified using investors' expectations of the market than using risks associated with bank liquidity.

Most recently, the importance of information flow in the build-up of financial crisis was explained with 'order-disorder phase transition', a term adopted by Bossomaier et al. (2018). During stable periods, markets become disordered due to heterogeneity in investors' information-based decision-making process. In contrast, both exogenous and endogenous crises stimulate coordinated and collective decision-making with individual investors, bringing more order to the market (i.e., an exogenous crisis is crisis generated elsewhere whereas an endogenous crisis is crisis generated within the system). Here, endogenous crisis is likely to represent an amplification in mutual information sharing among investors (Matsuda et al., 1996; Gu et al., 2007; Barnett et al., 2013) .

A predictive indicator that would amplify before transitioning into a crisis is longed for in the literature. **In line with that purpose, our information transmission maps presented in chapter 5, visually discern endogenous and exogenous crises. Exogenous crises are mapped with small reinforcing circles as laid out in Muir (2017), whereas the abnormalities in nonlinear clustering represented with contrasting colours indicate endogenous crises.** The economic prior underlying the closed circles address the undirected cyclic graph, a process involving a unique neural connectedness feeding off each other within random patterns. The identification of unique cycles bears some evidence, but only if such cyclic shapes suggest the onset of a crisis propagation.

2.8.2 Risk perception

A major problem with including the dynamic stochastic general equilibrium models in the 'efficient market hypothesis' is that they rule out the possibility of a crisis trying to model a 'frictionless' market. In an attempt to include crises and examine the responses to crises, 'agent-based models' evolved from the research by Farmer and Foley (2009). The authors ran simulations that subjected these agents to different scenarios that were governed by the agents' behaviour. These simulations generated different outcomes concerning human learning and adoption, but remained oblivious to other traits inherent in human nature. Further, the paradigm around 'rational expectation theory' does not hold, as all recent crises show evidence of overconfidence, fear and asymmetric information that influenced investors' responses to crisis and often exacerbated it. Past constraints have been overcome given the intertwining nature of financial products spanning across the world in real time and faster access to readily available information (or misinformation) in a modern world, but have also invoked higher 'frictions' than was previously conceivable.

The findings from the literature review lead to the need to answer some fundamental questions. For example, why do investors prefer risk over rational expectation? What makes investors take more risks, or does it?

Lo (2011) attempted to shed some light on what drives investors using neuroeconomics, an often understudied aspect of mainstream economics, to attempt to rationalise investor behaviour. The author found that any degree of monetary gain stimulated dopamine circling through participants' veins, triggering a reward circuitry similar to when using cocaine. While under normal conditions, our education and experience override our biological constraints, more emotionally charged situations drive a large population to react in ways similar to that described by Lo (2011). Lo (2011) described, just as fire sales are triggered by fears of extreme losses, imbalances in the level of dopamine release cause investors to take higher risks. Alternatively, risk-taking is associated with financial gains resulting from a series of lucky draws, leading to a potentially destructive positive feedback loop. It is evident from the GFC that investors are mostly oblivious to the risks they undertake, inasmuch as a widespread sense of security prevails. These securities may come from an influx of insurance, higher ratings on investment products or government bailout guarantees. In contrast, neuroeconomics provide evidence of investors' processing their sense of risk aversion in the same circuitry responsible for processing viscerally disgusting situations. Hence, it can be reasonably said that under extreme conditions, human behaviour is highly predictive of, and driven by, information or fear relating to potential losses, like investors who prefer higher risks (Lo, 2011). We will re-examine these stipulations in Chapter 5.

The last remaining question concerns the effectiveness of rational expectation. Behavioural biases and emotions are the basic blocks of investor behaviour; if severed, they may impair the decision-making process entirely. Rational expectation and other agent-based models assume investors can parse information effectively, and that has considerable economic implications. However, it is almost impossible for an average investor to conceive the correct response to other investors reacting to available information, which often requires five layer processing of information by these investors (Lo, 2011). Thus, 'rational' behaviour is more like a complex balancing act subject to the changing environment. In all, it has been proven that facing a strong emotional stimulus, logical deductions impair while predictable moves in investment prevails. Ignoring this basic phenomenon, economic models focusing on rational expectation or other agent-based simulations yield no success in the advent of recent crises.

Alessi and Detken (2011) suggested that a simple model of risk-taking can yield more control as a crisis transpires. Often, intervention by increasing policy rates may sufficiently break investor herding, and stems a falling market. However, an asset price boom–bust may even prove beneficial for middle-income countries. The increase in asset prices in a boom phase sufficiently offsets return losses in a bust phase, which cannot be held as true for advanced countries' markets. **This explains the less aggressive nature of the lower-income countries' markets, as sure profits often sever the trigger for a middle-income country facing a systemic crisis in advanced economies. We partly address this question in Chapter 5.**

Lee et al. (2015) also invoked the phenomenon of risk aversion to explain the determining factors of risk premiums. They argued for the importance of investors' risk preferences to determine asset pricing, active reallocation of assets in a portfolio and the varying degree of risk management. Hurd et al. (2011) suggested that active portfolio reallocation is determined mostly by systematic variations in assets, reflecting investors' risk preferences. **The lack of empirical evidence concerning risk preference during crisis provides a natural experiment for us to disentangle the dynamics of risk aversion in association with exogenous shocks and systemic risk effects, in chapter 5.** By doing so, we gain further insights into the role and evolution of the degree of investors' risk preferences in the pre, during and post-crisis periods.

We conjecture that risk perception precedes crisis propagation. Risk perception is often driven by full or partial information, which helps us to identify and predict crisis transmission patterns without making data-driven crisis predictions. The efficacy of the models we use proves that a pattern exists in information flow/risk-taking prior to a realised crisis, allowing us to propose an ex-ante crisis detection system.

2.9 SOM / Risk topography

Brunnermeier et al. (2012) highlighted the usability of financial data that underlies systemic risk patterns with risk topography. Risk topography actually informs policymakers and market makers about systemic risk, which prevails in the market and investment portfolios. This has substantial implications for regulatory risk assessment and private risk management. Moreover, risk topography allows regulators to detect liquidity sensitivity in the market facing different liquidity conditions, as sensitivity of the market participants to different extreme conditions is reflected in the detectable market risk trends. Crucially, finding predictive patterns in financial markets is at odds with the efficient market hypothesis and with some equilibrium relationships, even when one considers incomplete markets with informational asymmetries. Yet, this general equilibrium, macro modelling exercise implies the best use of financial data to identify systemic risk and crisis. Although a crisis may trigger due to a range of reasons, there lies a commonality in the patterns of crisis propagation. **We produce a risk topography in Chapters 3 and 5.**

The literature making use of ANN in systemic risk pattern recognition taking advantage of Self Organizing Maps (SOM) is new. Similar application is found only in Sarlin and Peltonen (2013). The approach allows monitoring of channels of crisis transmission, visualizing of vulnerability patterns in a closed system, and proposes an early warning system for possible crisis transmission effects. Betz et al. (2014) showed that SOM has superior prediction properties than traditional latent models based on early learning systems in predicting crises.

We adapt the SOM approach to include estimated unconditional spillover measures into the crisis maps in chapters 3 and 5 - the original Sarlin and Peltonen (2013) maps are calibrated, rather than drawn from estimated relationships. The crisis maps indicate the propagation of a crisis from one position in the 'state space' to adjacent locations of the financial stability neighborhood, allowing us to map instabilities throughout connected global markets. More generally, the use of crisis maps allow us to connect the ANN approach to existing concepts of financial stability. Earlier papers using ANN for crisis prediction include Liu and Lindholm (2006); Peltonen (2006); Apolloni et al. (2009); Marghescu et al. (2010); Betz et al. (2014), and for network mapping see Barthélemy (2011); Sarlin and Peltonen (2013); and very recently for the clustering of capital markets with SOM, see Resta (2016). Finally, this system enhances our capacity to recognize the direction of induced vulnerability if a crisis ensues. The maps represent a new frontier in the usage of systemic risk and dynamic network estimates.

Orthogonal stress scenarios can be specified within the broad classes of market risk and idiosyncratic risk. Changes in interest rate, policy rate and in the rates of public debt presents the market with the first stress scenario [3]. Changes in stock prices, commodity prices, house prices, credit derivative indices [4], and exchange rates indicate a burgeoning credit crisis. Finally, a liquidity risk scenario disproportionately affects financial institutions and in its height results in rate hikes and shutdowns of the securitisation market. Any allowable conclusion must include that systemic risk does not yield reliable information if the endogenous responses of

[3] This class of stress scenario includes changes in swap rates, eg LIBOR, HIBOR, FIBOR, PIBOR etc

[4] LCDX, CMBX, CDX

market participants are not diagnosed.

Connecting the dots and concluding remarks

We provide evidence of a strong connection between the aforementioned streams of studies in the Figure 2.1, Figure 2.2, Figure 2.3 and Figure 2.4. For this purpose we use a combination of network algorithms proposed by Fruchterman and Reingold (1991); Jacomy et al. (2014) and Hu and Shi (2015).

From figure 2.1 it is evident that a strong relationship between systemic risk and financial contagion and financial network papers prevail. However, a specific focus towards equity systemic risk connects the other three tenets of the studies and extends the connections upto securitisation, feedback loop and risk taking behavior.

From figure 2.2 it is evident that financial crisis literature is central in the relevant literature as addressing different facets of systemic financial crisis is dominates as the key argument for streams of studies concerning financial crisis, systemic risk, securitisation, equity and banking risk argument, feedback loops, financial contagion,financial networks, risk perception subject to changes in information and risk topography. Yet, up until now, crucial literature did not attempt to combine insights from these streams of studies in order to solve the issue of predicting and controlling crisis transmission. In the current thesis, we aim to solve this issue of crisis by taking a balanced approach considering the strong connectivity between these streams of studies.

Figure 2.3 furthers the argument regrading the coupling of these tenets of studies by presenting a spherical diagram. Figure 2.4 delves into the cross citation network and finds crucial literature that connects these tenets more than others lie around Glasserman and Li (2005); Covitz et al. (2009); Stein (2010); Gai and Kapadia (2010); Alessi and Detken (2011); Shleifer and Vishny (2011); Bisias et al. (2012); Acemoglu et al. (2015); Glasserman and Young (2015); Giraitis et al. (2016); Betz et al. (2016); Resta (2016); Krishnamurthy and Muir (2017b); Dungey and Renault (2018); Dungey et al. (2020) etc. Notably, these studies bridge the gap between the other streams while attempting to address systemic crisis.

Table 2.1 presents a complete classification of all tenets sourced from similar studies. Despite taking different directions, the studies in Table 2.1 aimed to contribute broadly to crisis identification and mitigation research. Table 2.2 highlights the limitations in the crucial extant literature.

In the current thesis, we address these gaps in the following chapters and take advantage of the connections described here to devise our systemic risk identification and prediction framework.

Table 2.1: Taxonomy on the basis of concentration of studies

Classification by focus	
Focus	Literature
Financial crisis [5]	Myers (1977); Morrow (1997); Kaminsky et al. (1998); Backus et al. (1999); Barbieri and Levy (1999); Borio et al. (2001); Nordhaus (2002); Li and Sacko (2002); Barbieri (2002); Leigh et al. (2003); Leach (2003); Kaminsky et al. (2003); Rigobon and Sack (2005); Schneider and Troeger (2006a,b); Dooley and Hutchison (2009); Brunnermeier et al. (2009); Reinhart and Rogoff (2009); Borio and Drehmann (2009); Alessi and Detken (2009); Diamond and Rajan (2009); Bordo and Haubrich (2010); Shleifer and Vishny (2010); Khandani et al. (2010); Moosa (2010); Alessi and Detken (2011); Borio (2011); Aloui et al. (2011); Chudik and Fratzscher (2011); Saurina and Repullo (2011); Samarakoon (2011); Min and Hwang (2012); Guo et al. (2011); Neaime (2012); Celık (2012); Billio et al. (2012); Gallegati (2012); Hoesli and Reka (2013); Drehmann and Juselius (2014); Chittedi (2014); He and Krishnamurthy (2014b); Jung and Maderitsch (2014); Dungey et al. (2015); Raghavan and Dungey (2015); Flavin and Sheenan (2015); Anderson et al. (2015); Ruščáková and Semančíková (2016); Elliott and Timmermann (2016); Jin and An (2016); Rotta and Valls Pereira (2016); Ye et al. (2016); Hemche et al. (2016); Hermansen and Röhn (2017); Bordo and Haubrich (2017); Cont and Schaanning (2017); Fry-McKibbin and Hsiao (2018); Fry-McKibbin et al. (2019); Dungey et al. (2020)

Continued on next page

Table 2.1: Classification by focus

Classification by focus	
Focus	Literature
Systemic risk [6]	Grubel and Fadner (1971); King and Wadhwani (1990); Granger (1992); Shrieves and Dahl (1992); Shaffer et al. (1994); King et al. (1994); Field (2003); Forbes and Rigobon (2001, 2002); Collins and Biekpe (2003); Sbracia and Zaghini (2003); Kashyap et al. (2004); Brooks and Del Negro (2005); Elsinger et al. (2006b); Brunnermeier and Pedersen (2008); Diebold and Yilmaz (2009); Covitz et al. (2009); Fama and French (2010); BIS (2010b); Billio et al. (2010); Allen and Carletti (2010); Wagner (2010); Puri et al. (2011); Kritzman et al. (2011); Hanson et al. (2011); Eiling and Gerard (2011); Adrian and Brunnermeier (2011); Acharya et al. (2012); Battiston et al. (2012); Diebold and Yilmaz (2012); Allen et al. (2012); Khandani et al. (2013a); De Bruyckere et al. (2013a); Abdymomunov (2013); Duffie (2013); Patro et al. (2013); Antonakakis and Vergos (2013); Kalemli-Ozcan et al. (2013); Elliott et al. (2014); Grilli et al. (2014); Papanikolaou and Wolff (2014); Dungey and Gajurel (2014); Greenwood et al. (2015); Kim et al. (2015); Duarte and Eisenbach (2018); Glasserman and Young (2015); Romer and Romer (2015); Danielsson et al. (2016); Tobias and Brunnermeier (2016); Chang (2016); Brownlees and Engle (2016); Yang et al. (2016); Calabrese et al. (2017); Shenoy and Williams (2017); Diebold et al. (2017a); Gonzalez et al. (2017); Brownlees et al. (2017); Chiang et al. (2017); Dungey et al. (2018a); Badshah (2018a); Grant and Yung (2017); Malik and Xu (2017); Liu et al. (2017); Vergote (2016); Engle (2018)

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Table 2.1: Classification by focus

Classification by focus	
Focus	Literature
Securitisation sourced crisis	Pennacchi (1988); Hughes et al. (1999); DeYoung et al. (2001); Allen and Gale (2004); Allen and Carletti (2006); Elsinger et al. (2006a); Acharya and Yorulmazer (2007); Deng et al. (2007); Adrian and Shin (2008, 2009); Covitz et al. (2009); Shin (2009); Hakenes and Schnabel (2010); Pozsar et al. (2010); Stein (2010); Shleifer and Vishny (2010); Uhde and Michalak (2010); Nijskens and Wagner (2011); Diamond and Rajan (2011); Nadauld and Weisbach (2012); Bedendo and Bruno (2012); Gorton and Metrick (2012); Georg (2013); Battaglia and Gallo (2013); Berger and Bouwman (2013); Acharya et al. (2013); Moreira and Savov (2014); Battaglia et al. (2014); Chen et al. (2017); Mersch (2017); Bakoush et al. (2019a)
Feedback loop[7]	Allen and Carletti (2006); Liu and Lindholm (2006); Peltonen (2006); Apolloni et al. (2009); Atsalakis and Valavanis (2009); Davis et al. (2010); Vaisla and Bhatt (2010); Candelon and Palm (2010); Marghescu et al. (2010); Ferreira and Santa-Clara (2011); Barthélemy (2011); Brunnermeier et al. (2012); Angeloni and Wolff (2012); De Bruyckere et al. (2013b); Sarlin and Peltonen (2013); Wilcox and Fabozzi (2013); Antonakakis and Vergos (2013); Claeys and Vašíček (2014); Betz et al. (2014); Acemoglu et al. (2015); Acharya and Steffen (2015); Brunnermeier et al. (2016); Resta (2016); Joseph et al. (2016); Chen et al. (2016); Farhi and Tirole (2017); Joseph et al. (2017); León et al. (2017); Krishnamurthy and Muir (2017b); Zhong and Enke (2017); Dungey et al. (2019)

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Table 2.1: Classification by focus

Classification by focus	
Focus	Literature
Contagion	Kindleberger (1978); Hamao et al. (1990); Lin et al. (1994); Longin and Solnik (1995); Holmstrom and Tirole (1996); Eichengreen et al. (1996); Holmstrom and Tirole (1997); Kiyotaki and Moore (1997); Goldstein (1998b); Masson (1998); Allen and Gale (1998); Eichengreen and Hausmann (1999); Ang and Bekaert (1999); Masson (1999); Dornbusch et al. (2000); Dungey and Martin (2001); Kyle and Xiong (2001); Bordo et al. (2001); Forbes and Rigobon (2002); Billio and Pelizzon (2003); Flavin et al. (2008); Lucey and Voronkova (2008); Duffie et al. (2009); Dooley and Hutchison (2009); Farmer and Foley (2009); Gai and Kapadia (2010); Syllignakis and Kouretas (2010, 2011); Kazi et al. (2011); Shleifer and Vishny (2011); Chudik and Fratzscher (2011); Gai et al. (2011); Longstaff and Wang (2012); Calomiris et al. (2012); Van Binsbergen et al. (2012, 2013); Bekaert et al. (2013); Mink and De Haan (2013); Dimitriou and Simos (2013); Mondria and Quintana-Domeque (2013); Caccioli et al. (2014); Bekiros (2014); Elliott et al. (2014); Kazi et al. (2014); Acharya and Bisin (2014); I. Dimitriou and M. Simos (2014); Glover and Richards-Shubik (2014); Jobst (2014); Wang (2014); Dungey et al. (2014); Kenourgios and Dimitriou (2015); Shen et al. (2015); Dungey and Gajurel (2015); Belo et al. (2015); Darolles and Gourieroux (2015); Shen et al. (2015); Syriopoulos et al. (2015); Lin et al. (2015); Cont and Wagalath (2016); Jayech (2016); Piccotti (2017); Shenoy and Williams (2017); Seth and Panda (2018); Dungey and Renault (2018)
Financial network	Myers (1977); Freixas et al. (2000); Allen and Gale (2000); Haldane (2009); Khandani and Lo (2011); Ibragimov et al. (2011); Gai et al. (2011); Hanson et al. (2011); Allen et al. (2012); Acemoglu et al. (2012); Battiston et al. (2012); Haldane (2013); Elliott et al. (2014); Diebold and Yılmaz (2014, 2015); Hautsch et al. (2014); Elliott et al. (2014); Acemoglu et al. (2015); Giraitis et al. (2016); Resta (2016); Dungey et al. (2017a); Cabrales et al. (2017); Dungey et al. (2018b,a, 2020)

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Table 2.1: Classification by focus

Classification by focus	
Focus	Literature
Risk perception/ information transmission	Hicks (1936); Harrod (1939); Lachmann (1943); Muth (1961); Samuelson (1965); Malkiel and Fama (1970); McCallum (1976); Lucas et al. (1976); Neary and Stiglitz (1979); Wallis (1980); Diamond (1984); Fazzari (1985); Diamond and Verrecchia (1987); Matsuda et al. (1996); Fleming et al. (1998); Kodres and Pritsker (2002); Kumar and Persaud (2002); Getmansky et al. (2004); Corsetti et al. (2005); Boyer et al. (2006); Chiang et al. (2007); Gu et al. (2007); Khandani et al. (2010); Dungey et al. (2010b); Dooley and Hutchison (2009); Stein (2010); Diamond and Rajan (2011); Lo (2011); Hurd et al. (2011); Malmendier and Nagel (2011); Syllignakis and Kouretas (2011); Alessi and Detken (2011); Celık (2012); Barnett et al. (2013); Lehkonen and Heimonen (2014); Lee et al. (2015); Barberis et al. (2015); Kocaarslan et al. (2017); Bossomaier et al. (2018)

[5] Includes credit crisis, liquidity spirals, financial and leverage cycles, early warning indicators and other macroeconomic studies

[6] Includes micro and macro prudential risk measures

[7] Includes topography and crisis prediction

Table 2.2: Critical Review Matrix

Critical Review			
Author	Objective of the study	Significance	Limitations
Alfaro and Drehmann (2009)	Banking Crisis- crisis and real growth	This paper highlighted that stress scenarios based on historical data are misleading if macro conditions prior to a crisis are troubled. Also, statistical structure of stress testing models may become inconsistent during a crisis.	The paper did not include crucial risk factors underlying international linkages. Stress tests should also consider endogenous cycles underlying a crisis. This subjected the proposed methods to structural limitations (we address this gap in Chapter 3).
Khandani and Lo (2011)	Forecasting credit default and delinquencies - macro - banking consumer/credit risk	The authors proposed a machine-learning model for consumer credit default, forecasting credit events several months in advance. Authors suggested aggregated consumer credit-risk analysis is imperative in forecasting systemic risk.	The inferences are mostly indirect, tentative and speculative. Empirical findings are based on simple methods representing only certain short-term, market-neutral, mean reversion strategies applied to USA markets. Inferences are not a good proxy for long/short equity products involving USA and international equities and other securities. Although the hypothesis that an unwind initiated losses during the second week of August 2007 is correct, little can be said about the ultimate causes of such an unwind.

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Table 2.2: Critical Review Matrix

Critical Review			
Author	Objective of the study	Significance	Limitations
Alessi and Detken (2011)	Early warning risk measure - equity	The paper examined signalling approaches predicting asset price booms for 18 OECD countries since the 1970s. The paper highlighted that financial variables contain more information for predicting costly asset price booms than the real indicators. Global financial indicators perform better than domestic ones.	It is more practical to say that even equally well-performing indicators can relay different messages. The yielded signals should only be considered one of several inputs to the information set of decision-makers. (We partly address this issue by producing information indices with stochastic dynamic general equilibrium models in Chapter 5.)
Kritzman et al. (2011)	Systemic risk/ absorption ratio - equity	The authors introduced a systemic risk measure termed absorption ratio. A high absorption ratio implies that markets are compact. Compact markets are more fragile, as shocks propagate more quickly and broadly. Alternatively, a low absorption ratio is suggestive of less tightly coupled, and so less vulnerable, markets.	Although absorption ratio spikes precede most significant stock market drawdowns, coupled markets do not always shows asset depreciation. This suggests that spikes in the absorption are not a sufficient condition for all market drawdowns.
Kapadia et al. (2012)	Liquidity crisis and Contagion - banking	The authors provided a quantitative framework showing how shocks to fundamentals may interact with funding liquidity risk and potentially generate contagion.	The authors concurred that with better data, more detailed analysis of liquidity feedbacks may yield better results. (We use simple uniform data for the entire thesis.)

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Table 2.2: Critical Review Matrix

Critical Review			
Author	Objective of the study	Significance	Limitations
Acharya et al. (2012)	Banking crisis- equity and credit default swap	The paper proposed various systemic risk measures such as SES, MES and LVG. The authors explained how ex-ante measures of systemic risk can predict the ex-post losses during the financial crisis of 2007–2009.	The paper focused its methods only on the GFC. The paper could have extended for a longer period to check for the dynamics in stress building across international financial institutions as well. The connectivity factor in risk analysis was constrained due to the small sample used. (We partly address this gap by applying simple general indices and large samples.)
Khandani et al. (2013a)	Unwinding Hypothesis - equity hedge funds	In August 2007, many long/short equity hedge funds in the USA market suffered unprecedented losses. It was hypothesised that such temporary dislocation was caused by a coordinated deleveraging of similarly constructed portfolios. The authors simulated the returns of these portfolios and found evidence that the unwinding began in July 2007 and continued up until the end of that year.	The span of data covered was very specific. Suggestions were derived based on analysis of the USA hedge fund industry only. International connectivity was completely overlooked. (We partly address this gap by considering international connectivity across a fair range of countries.)
Sarlin and Peltonen (2013)	Early warning signals- equity	This aim of this study was to Incorporate modern mapping into financial economies. This allowed high-dimensional representations projected on low-dimensional display, which allowed for disentangling potential vulnerability in a system.	The usage of mapping can only be rational when such methods are nested with other nonlinear dynamic models. Similar questions were asked in Resta (2016); Betz et al. (2014).((We partly address this issue by nesting dynamic mapping with nonlinear dynamic models as reflected in deep unsupervised learning models.)

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Table 2.2: Critical Review Matrix

Critical Review			
Author	Objective of the study	Significance	Limitations
He and Krishnamurthy (2014a)	Systemic risk- financial intermediation	Systemic risk arises when shocks lead to states in which a disruption in financial intermediation adversely affects the economy and feeds back into further disrupting financial intermediation. This paper presented a macro-economic model with a financial intermediary sector subject to an equity capital constraint. The novelty is that the model produced a stochastic steady state distribution for the economy, in which only some of the states corresponded to systemic risk states. The model examined the transition from 'normal' states to systemic risk states.	The model was quantitatively lacking on other dimensions. The model had only two state variables. One cost of this simplicity is that there was no labour margin in the model and so measures, such as hours worked, were missing. In the sample USA data, the only significant financial crisis was the 2007–2009 crisis. The model showed replication of data patterns corresponding to the GFC only. (In Chapters 3, 4 and 5, we provide justification for our model's efficacy for crisis demarcation across a wide range of financial crises.)
Acemoglu et al. (2015)	Network and systemic risk- banking	This paper proposed a tractable framework focusing on what shapes the contemporaneous relationship between existing network architecture and the structure of systemic risk. The authors argued that financial institutions that are located in the centre of networks commanding high systemic risk are crucial in containing crisis. Bailing out such institutions can be the first step in containing contagion.	This paper focused on the architecture underlying counterparty risk via debt contracts. This paper did not discuss other financial intermediaries that may potentially instigate contagion, including fire sales or liquidity withdrawal.

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Table 2.2: Critical Review Matrix

Critical Review			
Author	Objective of the study	Significance	Limitations
Bonaldi et al. (2015)	Financial network- banking	The authors proposed a method for estimating spillovers between funding costs of individual banks. The method used an elastic net estimator for measuring financial connectedness. The authors claimed that this measure was directly related to the importance of a bank in this network.	This paper focused on the global financial crisis only to identify vulnerabilities induced in this model. (We address this issue by focusing on a wide range of crises in this thesis.)
Dungey and Gajurel (2015)	Contagion- equity, bond and REIT returns	This paper proposed a methodology to endogenously date crisis period while identifying contagion effects. The method was data driven and allowed for examination of the evolution of markets from calm to crisis period.	The method did not distinguish between external and internal contagion. Hence, it is likely that inter-temporal volatility spikes may have overshadowed actual contagion effects.
Romer and Romer (2015)	Stress testing	This paper investigated financial distress for 24 advanced economies, focusing on post-crisis periods since 1967 until GFC period. Financial distress is classified in graduations, and a better chronology is offered.	The findings induce more questions than they answer. This paper did not investigate the issue of causation with respect to crisis. The paper is limited in investigating only advanced countries. The authors agreed that financial distress transpires differently for emerging economies. (We partly address these gaps in Chapters 3, 4 and 5.)

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Table 2.2: Critical Review Matrix

Critical Review			
Author	Objective of the study	Significance	Limitations
Brownlees and Engle (2016)	Capital shortfall/SRISK- U.S. financial institutions with a market capitalization greater than US 5 billion dollars as of the end of June 2007	Authors suggested systemic risk is determined by the capital shortfall generated by distressed institutions conditional on a systemic event. Authors claimed this framework is able to detect if a small number of large financial institutions pose systemic threats to the entire system.	This paper focused on large USA institutions by examining the proposed SRISK matrix. However, systemic risks due to interconnection within international financial institutions were not examined considering systemic risk a global phenomenon.
Tobias and Brunnermeier (2016)	Systemic risk - publicly traded financial institutions	The authors introduced CoVaR, 'the value at risk of the financial system conditional on institutions being under distress'. This paper attempted to quantify the extent to which factors such as leverage, size and maturity mismatch can be used for predicting systemic risk.	CoVaR presents a tail risk measure and as such considers a few extreme crisis data points. Any adverse conditions preceded by a stable period naturally leads to a spike in tail risk measures. This further reinforces the debate on 'too big to fail', suggesting that size matters and only large institutions should face more stringent regulations. This 'size only' approach does not acknowledge that small institutions can be very 'systemic as part of a herd'.
Cont and Schaanning (2017)	Fire sales and networks- banking	This paper presented a framework that quantifies fire sale effects in a network of financial institutions with common assets. The authors explained a feedback loop in asset price depreciation triggered by fire sale.	To perform a stress test, a leverage constraint corresponding to the Basel 3 leverage constraint was used. Alternative outcome may emerge using ratio of capital to risk-weighted assets as a constraint, or both. Due to the limitation in the dataset, stress testing with both the constraints was not present.

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Table 2.2: Critical Review Matrix

Critical Review			
Author	Objective of the study	Significance	Limitations
Engle (2018)	Early warning risk measure/ credit risk	In this article, authors presented new results on the uncertainty associated with the SRISK measure by comparing it with other related measures. It was found that SRISK increased substantially in Europe, but declines as the sovereign debt crisis subsided. SRISK was prevalent in both China and Japan over the last decade.	An aggregate factor that could have been derived from national capital market and the investors' preference factor was missing while discussing the stress scenario in global terms. (We explore this issue in Chapter 5.)
Baruník and Křehlík (2018)	Systemic Risk- equity	Authors presented a new connectedness measure induced due to heterogeneous frequency responses to shocks. This paper attempted to disentangle the sources of connectedness between variables by suggesting that shocks affect economic variables at different frequencies with varying strengths. Connectedness periods at high frequencies indicate stock market process information rapidly and calmly, and a systemic shock is short-lived. But at lower frequencies, systemic shocks are more persistent.	The efficacy of the method was examined only for the USA financial market. The intra-market connectivity technique was not very informative about global linkages or reactions to global sentiment.

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Table 2.2: Critical Review Matrix

Critical Review			
Author	Objective of the study	Significance	Limitations
Badshah (2018b)	Cross market volatility- equity	The paper examined cross-market volatility dependencies and spillovers in both moments of volatilities for emerging, developed and USA equity markets. The paper used several volatility indexes, including VIX, VXEFA and VXEEM. The study found significant cross-market volatility dependencies concerning USA and emerging markets. This reduced diversification benefits substantially.	This paper applied DCC models, whose efficacy is disputable. Syriopoulos et al. (2015) quoted that, 'despite the attractive properties of the DCC model, empirical estimation and interpretation can be seriously constrained by complexities due to excessive parameter requirements, biased estimates and convergence limitations over the estimation process, especially whenever additional exogenous variables are introduced into the conditional mean and variance specifications'. (We avoid using DCC models and rely on non-parametric approaches that can accommodate a large number of variables, allowing us to apply exogenous shocks without having biased estimates and order-invariant methods.)
Dungey and Renault (2018)	Contagion- equity and CDS	The authors argued that contagion identification often leads to a grey region, in that changing volatility in returns often over-forecasts measures of contagion. This paper proposed a framework to identify contagion, taking advantage of heteroskedasticity via conditional volatility. This method has the benefit of dimensionality, as it can measure contagion from multiple sources over any number of assets.	The inherent reflection problem required both economic and statistical evidence. A multi-factor model, if incorporated in the suggested approach, may have induced spurious heteroskedasticity, and as such was a 'parsimonious' approach. (We partly address this concern in Chapter 4.)

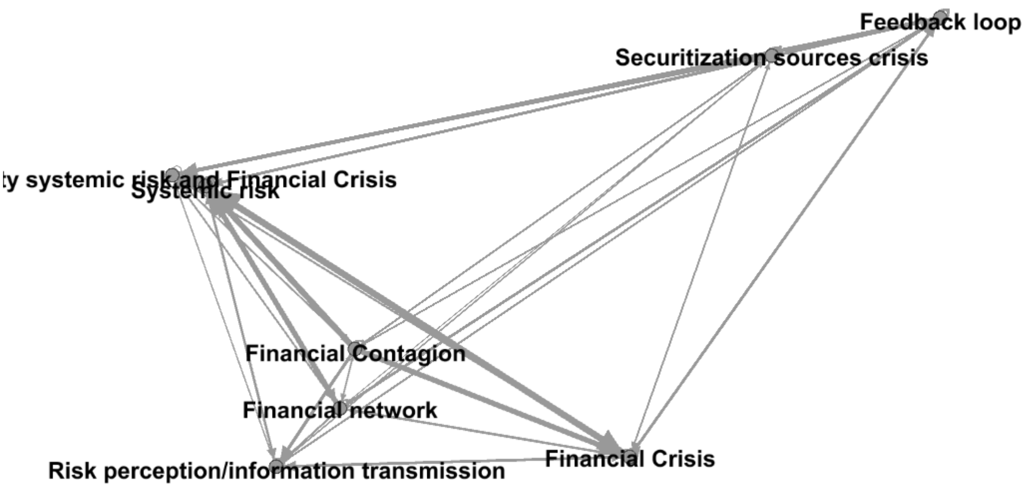


Figure 2.1: Literature network by streams of studies with ForceAtlas 2 algorithm
This figure represents the network connectivity between streams of studies targeting to solve the issue of systemic Financial crisis. The graph is drawn with ForeceAtlas 2 algorithm proposed for Gephi by Jacomy et al. (2014).

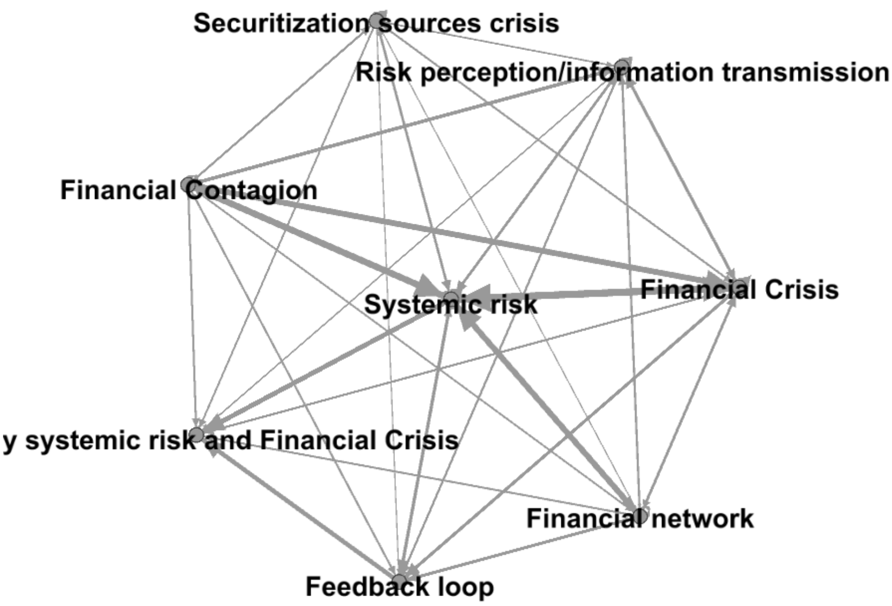


Figure 2.2: Literature network by streams of studies with Frutchterman Reingold algorithm. Note: This figure represents the network connectivity between streams of studies targeting to solve the issue of systemic Financial crisis. The graph is drawn with Frutchterman Reingold algorithm proposed by Fruchterman and Reingold (1991).

Figure 2.3: Literature network by streams of studies with Frutchterman Reingold algorithm. Note: This figure represents the network connectivity between major studies targeting to solve the issue of systemic Financial crisis. The graph is drawn with Frutchterman Reingold algorithm proposed byFruchterman and Reingold (1991).

Figure 2.4: Literature network by streams of studies with Frutchterman Reingold algorithm

This figure represents the network connectivity between major studies targeting to solve the issue of systemic Financial crisis. The graph is drawn with YiFan Hu proportional algorithm proposed by Hu and Shi (2015).

Chapter 3

Crisis Transmission: Visualizing Vulnerability

[This chapter is published in Pacific Basin Finance Journal, Volume 59, DOI: https://doi.org/10.1016/j.pacfin.2019.101255]

3.1 Introduction

Observed changes in correlation between asset returns during periods of stress have been variously attributed to contagion, spillovers and/or heightened vulnerability of networks. While the literature stretches back as early as King and Wadhwani (1990) on spillovers and Allen and Gale (1998) on contagion, the empirical work on networks and systemic risk/ connection is more recent. Systemic risk is the risk inherent in a system of closely connected entities, that can be cast as measure of crisis in the system. That is if triggered, can result in cascading down of the entities forming a global crisis situation. The structure implicit to systemic risk contains the degree of risks transmitted to others from one element and the degree of risks received by the element from others. This allows identification of nodes as either high spreaders or strong receivers within a closed system. The property of receiving shocks from others is closely related to the concept of the varying 'vulnerability' (Allen and Gale, 2000; Gai and Kapadia, 2010; Acemoglu et al., 2015). One of the most important predictions of the network literature demonstrates how financial sector networks can become 'vulnerable'. Shocks may spread dramatically via financial interconnectedness as 'vulnerability' affects otherwise 'robust' networks. Empirical representations show how the networks themselves change over time, between calm and crisis periods, and with the development and growth of emerging capital markets; see for example Billio et al. (2012); Khandani et al. (2013b); Capponi (2016); Chowdhury (2018). The changing nature of the links between institutions can itself be cast as a measure of contagion; see, Dungey et al. (2017b), while spillover indices can be obtained from network adjacency matrices proposed by Diebold and Yilmaz (2009).[1]

This chapter presents visualization of crisis transmission pathway in a system of financial network via recursive neural networks, largely known as Artificial Neural Networks (ANN). By considering the largest vulnerabilities in the ANN patterns we

[1]See applications and extensions in Demirer et al. (2018b); Yilmaz et al. (2018); Yilmaz (2017); Diebold et al. (2017b); Diebold and Yılmaz (2014, 2015)

produce crisis maps which highlight the least resistance shock transmission pathways at any point in time. They are somewhat analogous to slices of a brain scan lit up by firing neural pathways and as such are easily processed visually. We show how ANN methods relate to the commonly understood VAR representation and hence can be cast as an extension of the vulnerability representations with networks as in Diebold and Yılmaz (2014, 2015). The Self Organizing Maps used for this purpose **dictates** other methods in this area of studies, in that, the maps are produced with a recursive algorithm initiated with random vectors, executing relentlessly until repeating patterns are identified and classified. Self organizing maps are popularized as 'deep unsupervised learning'.

We estimate transmissions from systemic risk estimates, **which provides an easily accessible image of the pathways** which are most likely to transmit crisis shocks across the system at any point in time. This is used to draw two-dimensional maps of how these pathways change as a crisis, and its associated management plan progresses. Further, **we contribute** in the vein of early warning literature by presenting in-sample predictions of crisis building in our predefined system.

Our aim is to convincingly implement means by which managers of systemic risk can also simulate the effect of alternative intervention paths in a network and have some knowledge of where the most effective interventions may lie given the structure of the network at any point in time. Although we use existing data, **managers may decide to randomize inputs, altering expectations** or simply feed the networks with predictions to detect alternative transmission pathways. Thus, **we specifically acknowledge** the conditional nature of the problem, and that intervention strategies may need to be flexible and time-varying, responding to the changing structure of the network and the many alternative possible sources of shocks.

We identify the most crisis-prone markets and explain how the impact of innovations in those markets differ from those in markets which are less crisis-prone. The inclusion of oil exporting markets, during periods where conflict affected oil supplies allows us to examine the sensitivity of the global system to volatility and shocks from these sources.

We address six key questions concerning the time varying nature of systemic risk estimates leading to the detection of crisis transmission patterns. First, we examine whether policy interventions which restrict significant transmission paths help interconnected markets weather shocks. Second, we find that the changing interactions between markets results in changing patterns in risk transmission. Third, we examine whether it is possible to detect which markets are more shock resistant in the sample period from 1998-2017. Fourth, we cut individual pairwise links off from the structural parameter estimates and identify if this reduces vulnerability/resilience. Fifth, we produce time varying crisis transmission pathway maps for a predefined system. We illustrate the changing dynamics in risk transmission, and show how this visualization helps to highlight the contemporaneous contagion and spillover effects using self organizing crisis-maps . Finally, we examine if completing a feedback loop for a cluster spill risks to the other clusters Davis et al. (2010), and hence if prediction of such in the patterns warns us of ensuing crisis in the system.

This chapter considers a broad set of global equity indices, investigating their complex interconnections. We first make use of the robust DY measure to investigate the contribution of each individual market onto all other markets, and highlight events associated with systemic network instability in the empirical evidence.

An important concern arising from the listed questions may be, why these questions are important or how they connect to a key logical argument that enhances our state of knowledge. Here, we build on the growing literature on time varying systemic risks, lying within complex market networks (Giraitis et al., 2016; Diebold and Yılmaz, 2015, 2014) that underpins modern economic network theories (Anufriev and Panchenko, 2015; Glover and Richards-Shubik, 2014). We propose a new perspective into crisis detection with stress classification. We contribute to the state of knowledge in regards to crisis pattern prediction, by limiting the gaps in similar fundamental techniques present in extant literature and improve upon those limitation.

In identifying crisis transmission pathway patterns while making predictions on crisis buildup we complement Sarlin and Peltonen (2013); Resta (2016). We propose a 'crisis-map' similar to the map of Sarlin and Peltonen (2013), but compiled with connectedness measures. This is a new use of SOM to better understand risk transmission pathway. Earlier, Duffie (2013) proposed a risk topography with a 10 by 10 by 10 approach. We countenance Duffie (2013) by proposing a 31 by 30 by 30 approach. In technical terms, the stress topology in the maps are highlighted with a grid of 30 by 30 classification nodes for each data point in the rolled over DY systemic risk index across entire sample period, allowing us to visualize a gradual shift to crisis from non-crisis. The 70-30 split of input data into train and test data allows us to incorporate in-sample predictions in the dynamic stress topology, while comparing the crisis occurrences in real time and with unconditional spillover signals.

To our knowledge, no other work has attempted to detect dynamic stress generation by combining network topology and crisis transmission pathway predictions measured from DY systemic risk index.

3.2 Empirical Framework

The Diebold and Yilmaz (2012) (DY) spillover methodology distinguishes spillovers between markets using VAR forecast error variance decomposition (FEVD). The FEVD matrix is used as the adjacency matrix (or 'connectedness matrix') between N co-variance stationary variables with orthogonal shocks; net pairwise return spillovers between assets form the elements of the bi-variate relationships between the markets in a network. The overall spillover index is formed by adding all the non-diagonal elements of the decomposition.

From a VAR(p) of the form[2]

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-i} + \varepsilon_t \tag{3.1}$$

where x_t is a vector of stock returns, $x_t = (x_{1t,\ldots.} x_{Nt})'$, φ_i is a squared parameter matrix and $\varepsilon_t \sim \mathrm{N}(0,\, \Sigma)$. The corresponding moving average representation is

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i.} \tag{3.2}$$

[2]The intercept is suppressed for simplicity and without loss of generality.

in which,

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots + \phi_H A_{i-H}.$$

To circumvent the order variation issue Diebold and Yılmaz (2014) use generalized H-step-ahead forecast error variance decomposition, (where H is user defined), constructed exploiting the generalized VAR framework (GVD) of Koop et al. (1996). This is denoted by $\theta_{ij}^{g}(H)$ and given as

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{3.3}$$

where Σ is the variance co-variance matrix, σ_{jj} is the standard deviation of error term for jth equation, A_h is the coefficient matrix in the infinite moving average representation from VAR. At this stage, $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$.

Normalizing each row of the adjacency matrix gives

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}. \tag{3.4}$$

By construction $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. DY index captures the full sample static spillover by measuring the sum of off-diagonal elements as a proportion of the sum of all elements as the system-wide connectedness. The directional spillover index identifies variance spillovers of all other markets to market i as

$$S_{i \leftarrow all}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{3.5}$$

and the reverse directional spillover measures volatility spillover from market i to all other markets similarly as $S_{i \rightarrow all}$, generating $\tilde{\theta}_{ji}^{g}(H)$ parameters.

The net pairwise spillover or pairwise directional connectedness identifies gross shock transmission TO and FROM sample markets. The net spillover between markets i and j is defined as

$$S_{ij}^{net}(H) = S_{i \rightarrow j}(H) - S_{j \rightarrow i}(H). \tag{3.6}$$

In other words, we compute the transmission and vulnerability matrices from pairwise directional connectedness matrices.

Common network statistics include measures for nodes concerning directional connectedness for links from other nodes as in-degree connectedness and measures of connectedness to other nodes as out-degree connectedness. System-wide connectedness can be measured via mean degree weight measures as in Diebold and Yılmaz (2014).

3.3 Crisis-Map Method

With the crisis-map we investigate crisis transmission in global equity indices, by showing how markets evolve during a crisis period. Changes in the location of nodes in euclidean space allows us to identify the possible pathways of lurking crisis in the system.

The self organizing crisis-map makes use of artificial neural network clustering in visualizing the data space. Essentially it implements a non linear projection from a potentially high dimensional input space onto a potentially lower dimensional array of nodes (nodes are also known as neurons in this literature), and as such represents a neural network. In principal, Self Organizing Maps attempt to preserve neighborhood relations by mapping from an n dimensional array of input vectors into a k dimensional array of output nodes. The process applies clustering techniques to assign nodes to their closest cluster via a number of steps. First, a lattice is populated with regular array of randomly generated synaptic weights or centers, in practice initialized with a PCA (Principal Component Analysis) surface. The iterative SOM algorithm, minimizes a loss function scanning across all data points in the input vector, and updates positions on the centers (weights) recursively. The updating process is initiated by reducing the distance, between the input vectors and randomly generated weight vectors, in other words, the loss function. Although, the position of input vectors remain unchanged, the synaptic weights are associated with nodes in the euclidean space. By finding the least distant input nodes from the synaptic weight vectors, we find the least distant nodes with input vectors in the neighborhood space, best known as the "Best Matching Units" (BMU). The algorithm works in neighbourhood space, so that closer neighbours have greater weight. This eventually results in a surface of weights resembling a sphere around the lattice. Updating and convergence may be achieved by using the usual gradient descent method. Finally, the non-linear structure of the data is fitted optimally around the lattice, shaping a sphere of clusters, that can be presented in a two dimensional grid of nodes. See Sarlin and Peltonen (2013) for a graphical representation of SOM.

In the process of dimensionality reduction with projection and clustering, SOM method also **produce robust predictions in the patterns outlined**. The process involves moving nodes across Euclidean space: predictors are organised for nodes (say for example equity indices where each return represents a node) and are grouped into intermediate vectors, which in this case are fewer in number than the initial input vectors (the intermediate step offers increased robustness to the crisis-maps). In other words, p distinct training vectors, equivalent to intermediate nodes are selected from the input data. Usually, the training data includes at least 80 percent of the sample data. The problem is represented by two dimensional array of predictions, a process involving random initialization of synaptic weights that we feed into the recursive optimization function, and an updating algorithm until the local minima for the loss function is achieved. The aforementioned updating algorithm leads to output nodes serving as prediction vectors or classifiers in unsupervised clustering. The nodes of the output vectors represent the topology that outlines the structure of the degree of temporal non-linear clustering in the data. The input and output nodes are connected via the weight vectors which project each node in the input vector onto another node in the output vector.

Notably, the iterative backward propagation algorithm has a convergence criterion as it generate weight vectors. Hence, the patterns produced in this process are **more robust then some contemporary methods** of stress detection in economics.

The process proceeds in five steps producing graphical representation of predictions and classifiers. First, a random weight matrix is generated. Second, the algorithm goes on selecting sets of input nodes and updating the weights via backward propagation (the analytic gradients of the weights construct the hidden layers of edges) and then updating the decay function which governs the relationship with neighbours. In each case the Best Matching Unit (BMU) is found by selecting the Euclidean norms, ε. The convergence criterion provides stability in the projection by centering the ε, that is looking for a total zero error. The visualization initiates at this stage with the decay function identifying sparsely connected nodes.

The neighborhood around the BMU follows an exponential decay function. The computational graph of this function takes up a similar structure as that of information processing within our brain neurons, hence the term neural network is loosely used.

$$\sigma_t = \sigma_0 exp^{\left(-t\lambda^{-1}\right)} \tag{3.7}$$

where, σ_0 is the lattice at time zero, t is the current period and λ is a conditional element. The purpose of the hyper-parameter is to regularize the decay function with penalty for non-convergence, reducing the complexity of the process. In the final stage, weight vectors continuously re-position with neighboring weights changing the most around BMU as reflected by the decay rate. The learning rate ξ decays with $\xi_t = \xi_0 exp^{\left(-t\lambda^{-1}\right)}$. Here, the one-step ahead weight function is represented as,

$$w_{t+1} = \omega_t + \theta_t \xi_t \varepsilon_t. \tag{3.8}$$

Finally, the neighborhood meets the convergence criteria (zero in theory), resulting in a lower dimensional response vector. The influence rate (this rate substitutes the largely known score function in generalized neural network architecture)

$$\theta_t = exp\left(-\frac{\varepsilon_t^2}{2\sigma_t^2}\right) \tag{3.9}$$

describes the degree of influence for each weight on the convergence. This rate is non-zero for the nearest neighbors to BMU decreasing with distance from BMU.

The neighborhood positions of the clusters in the crisis map represent contagion transmission complementing the approach of Sarlin and Peltonen (2013). In the crisis maps the degree of convergence are illuminated with darker to lighter colored grids resembling none to some degree of ensuing crisis. Failure of convergence indicates heightening of non-linearity between nodes, shown with cracks in the topology.

3.4 Data

We collect equity market indices from Datastream, pre-process the source data to control for missing values, estimate spillover indices and subsequently use the spillover indices as source data for 'crisis-maps'. Our raw data are daily dollar denominated price indices for 31 equities from Asia, Pacific, Europe, Americas and the Middle East, for the period beginning from 1st of January, 1998 up until 15th of September, 2017. This period includes at least 10 major episodes of financial stress as documented in Table 3.2.

We classify the markets into five clusters based on commonality in their economic indicators or common experiences with crisis. These are identified as Export Crisis (EC) markets - including markets which are heavily export oriented (oil and non-oil); oil exporters in terms of both emerging (OEE) and developed (OED) markets;

European markets directly affected by the Greek crisis of 2010 on-wards (GC), high-yield Asia-Pacific countries directly affected by the Asian crisis of 1997-98 (AC). By inclusion of the USA and Japan identified as conduit countries in global literature (BIS, 1998; Baur and Schulze, 2005), we aim to identify conduit effects in the system. The grouping of countries into each of these categories is shown in Table 3.1. Together with these indices our network incorporates the West Texas Intermediate (WTI) Oil Price Index for the inclusion of oil market conditions. We use S&P GSCI Commodity Return Index for commodity inclusion when applicable.

We transform the price indices to returns as the first difference of natural logarithms. Following Forbes and Rigobon (2002); Hyndman and Athanasopoulos (2014) we filter estimated returns with two day moving average to ameliorate the time zone effect on the data. Essentially, the moving average filter concentrates out the sharpest edge points, reducing white noise. This approach underpins much of the predictive and network literature; see for example Joseph et al. (2017); Zhong and Enke (2017); Elliott and Timmermann (2016); Chen et al. (2016); Ferreira and Santa-Clara (2011); Vaisla and Bhatt (2010); Atsalakis and Valavanis (2009); Cont (2001); Granger (1992); Balvers et al. (1990); Fama (1976).

Joseph et al. (2017) and Smith (1997) point out that, a moving average (MA) handles discrete time series more subtly than other approaches, despite its simplicity. Hence, we choose the moving average filter for signal processing. The correct choice of window size is important. We conduct multiple trials and find that window size 2 is a more robust choice, complementing the notion of Spectral Windowing presented in Oppenheim and Schafer (2014); Forbes and Rigobon (2002).

3.5 Empirical Results

In this section we present the results from estimating interconnectedness between the 31 equity indices with the transmission pathway outlined in crisis-maps.

First, we present the unconditional spillover generated from 31 equity markets and draw dynamic filtered financial networks. The financial networks highlight the highest transmitters and receivers. For better visualization we present spatial maps showing the highest to lowest transmitters and receivers identified with unconditional spillover measures.

3.5.1 Static Network

The estimated connectedness results for the full sample of 31 indices is shown in Table 3.3. An element in the i^{th} row and j^{th} column of the matrix gives the percentage contribution of the 10 day ahead forecast error variance decomposition to market i from market j. It clearly shows that the main source of shocks to each market are via own shocks on the main diagonal. Spillovers between markets are given by the off-diagonal elements. The total directional connectedness (from all others excluding own shocks) to i is found in the far right column of the table. The total connectedness to all others (excluding own shocks) from j is found in the bottom row of the column. These are the components of the DY index represented over the entire sample period.

Estimated vulnerability network plots are shown in Figure 3.1 and Figure 3.2 . The edges in these figures represent Euclidean distance between the nodes. We further filter both of the network plots to retain only the important linkages in the system. We use dynamic filtering of the static networks to retain links where the strength is over 100 and 50 percentage basis points, respectively in Figure 3.1 and Figure 3.2. We select the cutoff points by estimating the averages of weights in percentage basis points and then consider the upper points in the range. We use the force directed algorithm proposed by Fruchterman and Reingold (1991). This method has a strong theoretical foundation influenced by Multidimensional Scaling (MDS) theories. For more details see Fruchterman and Reingold (1991). This allows us to concentrate on the important network components of the system.

An appeal of the dynamic filtering is that it allows a more granular approach in explaining the degree and direction of changing systemic risks within networks. Figure 3.1, represents the links only when the shock transmission from the source nodes are higher than a maximum threshold of 100 points. The picture that emerges from the dynamic filtering highlights that Germany, Norway, Russia, Belgium, Canada, Sri-Lanka and the USA are the main transmitting markets. Specifically, the highest spillovers come from Germany and the USA to Australia, India and Iraq. The USA propagates its shock to China, and Germany transmits shocks to New Zealand.

When we explain the degree of transmissions between two nodes with GVD weights the euclidean distance between nodes account for the speed of transmission. We find that while Germany transmits a higher degree of risk to Japan and Kuwait than Australia euclidean distance suggests that a crisis transmits faster to Australia and Kuwait from Germany then to Japan. In other words, Japan will have more time to shift policies resisting the crisis reaching Japanese markets in the case of a crisis erupting in Germany, while Australia and Kuwait have considerably less time. The node locations also indicate that oil exporting markets in Middle East are highly vulnerable in terms of both degree and direction of crisis emerging from the USA and to a lesser degree from Russia. Interestingly, China is highly vulnerable only to a crisis erupting from the USA.

Figure 3.2 depicts vulnerabilities characterized by spillovers 'FROM' other markets. We filter out shock received from the source nodes if higher than maximum threshold (50% basis points).Figure 3.2 shows that Australia, Belgium, Austria, Germany, New Zealand and the UK are the most vulnerable to crises generated elsewhere. Some evidence is also provided on high vulnerability for China, Iraq, Kuwait, Sri Lanka and Canada. Figure 3.2 further shows that vulnerability nodes spread out further than transmission nodes. We interpret this as demonstrating the vulnerability of major markets to others, implying that with the emergence of a crisis, all markets will fall victim where the speed of transmission will vary with node distance.

Two dimensional networks represent a good way for presenting complex patterns. Yet, information is suppressed for limitations in the dimensions. We overcome these limitations by producing interactive three dimensional networks.(Three dimensional interactive networks cannot be produced in paper and is available upon request). With three dimensional networks, we find China and most middle eastern markets are close to each other while all other nodes are clustered in regards to both transmission and vulnerability.

3.5.2 Dynamic analysis

To analyze temporal risk associations among the markets, we construct the DY rolling sample indices to assess both transmission and vulnerability. Following Diebold and Yilmaz (2012) we begin by considering a 100 day rolling window to construct the Diebold and Yilmaz Connectedness Index (DYCI). We choose a 10 day ahead horizon, $H = 10$ for the forecast error variance decomposition, also consistent with Diebold and Yilmaz (2012). Diebold and Yilmaz (2012) demonstrated that the spillover indexes are not particularly sensitive to the choice of forecast horizon over 4 to 10 days. We retain the important edges by generating signals with 200 day moving average window.

Since the unfolding of the recent Russian ruble crisis leading to the dampening of global exports, investigations into the dynamic contemporaneous relationship between different markets have flourished (Capponi, 2016; Diebold et al., 2017b; Diebold and Yılmaz, 2015, 2014; Yilmaz et al., 2018; Demirer et al., 2018b; Liu et al., 2017; Malik and Xu, 2017; Vergote, 2016; Badshah, 2018a; Liow, 2015; Andrada-Félix et al., 2018; Ghulam and Doering, 2017; Chiang et al., 2017). We complement these studies by investigating the dynamics in a multi-cluster representation.

We classify the sample markets into Asian Crisis (AC), Export Crisis (EC), Greek Crisis (GC), Oil Exporting Emerging (OEE) and Oil Exporting Developed (OED) markets. We construct individual rolling indices for transmission and vulnerability and present them jointly.

In Table 3.2, we model all the crisis events across the sample period using DY rolling indices and find rational for important data points. Table 3.2 summarizes all the important edges in the figures presented in this section. Here we record the spikes in transmissions and vulnerabilities. Most often, a spike would shift the curves up to a new level and the curves remain upstream until a new spike emerges. This can be held also for a curve sliding downstream.

We plot the 'TO' and 'FROM' DY indices for AC & EC, OEE & OED and the GC markets together in Figures 3.3, 3.4, 3.5. Plotting the 'TO' and 'FROM' signals together for transmission and vulnerability allows us to examine whether a higher transmitter also exhibits strong vulnerability; or, if vulnerability is heightened more in response to a local event than a global one. We also examine whether the transmissions and vulnerabilities are counter-cyclical for specific markets.

In all the cases examined, and for the majority of the time period, the transmission estimates are higher than vulnerabilities. This points out that usually the contribution of own shock is dominant in explaining variations in any individual market's return, and the total impact of other countries is relatively small. The larger transmissions represent that all the markets are highly interconnected, since the total spillover to all others can be quite large despite individual (bi-variate pairwise) effect on others are relatively small; see Table 3.2.

The changing interconnectedness of the markets is clear from the results in Figures 3.3, 3.4, 3.5. Periods of crisis are distinguished in each of the panels of figures by a widening of the gap between transmission and vulnerability - transmissions tend to be higher and vulnerabilities - lower. The higher transmissions show when a market experiences crisis conditions it is more vulnerable to transmissions coming from other markets (this form of increased connectedness is denoted hypersensitivity in Dungey et al. (2010b). The lower vulnerabilities suggest the reduction in the effect of own shocks onto others during periods of turmoil.

Asian Crisis

During the Asian crisis of 1997-98 authorities resorted to different intervention strategies to stem the tide of crisis. Thailand adopted a structural adjustment package; Malaysia moved from a floating to fixed exchange rate regime; Indonesia adopted inflation targeting policy and moved to a floating exchange regime; the South Korean currency devalued and eventually floated, see Khan and Park (2009). Conversely, Singapore retained its managed currency float and China did not intervene.

Figure 3.3, shows transmission and vulnerability indices for the AC markets (India, Malaysia, Singapore, the Philippines, South Korea and Thailand). Our focus is on spillover effects, so own effects are excluded from our discussion. The contrast between the signals for Malaysia and Thailand provides a pertinent example of the features attributed to equity markets during the crises. Thailand is commonly viewed as the originator of shocks for the Asian crisis. This is also evident in its heightened transmissions at that time and again in the Global Financial crisis (GFC) period modelled in Figure 1, during the periods of increasing concerns over feedback effects on its economy. We find that both transmission and vulnerability amplifies for Thailand following the 2006 period. In contrast, Malaysia, was highly affected by the Asian Crisis, despite not being a crisis transmitter. It experienced a large increase in its transmissions at that point followed by decline in the relative effect.

The swings are much more substantial for India in the post Asian Crisis period (Indian data is sourced from Bombay Stock Exchange (BSE). BSE is not only the largest in the world in terms of a number of listed companies, it is also in the top 10 in terms of market capitalization). For both India and the Philippines, reversions quickly followed a spike in transmissions in the burgeoning GFC period.

Interestingly, the patterns for both Singapore and South Korea unveils a key finding. The signals point out that both the markets reflect a turning point in vulnerability appearing at the same time, between 2003-2004. Up until this point vulnerability decelerates gradually, rationalizing the benefits of flexible policy interventions in the post Asian crisis period, where a number of IMF programs and reforms were carried out over the late part of the previous decade. Vulnerability continued to amplify past the turning points for these markets.

In the post Asian crisis the decelerating cyclical patterns in crisis transmission and vulnerability supports the emergence of AC markets as safer investment venues relative to some other markets in our sample.

Export Crisis

The second panel in Figure 3.3 presents the exporting (EC) markets of Germany, Chile, France, China, UK and Australia. Higher transmission and vulnerability in EC markets correspond to the aftermath of drops in exports preceded by the Russian ruble crisis in 2014 following trade sanctions and military actions. Intuitively, the export crisis may also appear from the 2016 crude oil price drop.

We account for several key features extracted from Figure 3.3 in the vulnerability of systemic risks. We find a brief period of dampening that precedes further amplification for Germany at the same point as that of Singapore and Korea. Similar turning point is also detected in the Australian pattern but appearing much later. This suggests, that German transition is driven by the same force that exists for

Singapore and South Korea, whereas Australian transition reflects emanating GFC. Australia sees slowly reducing vulnerability and increasing transmission over the period. A second key feature is turning points in the curves of the UK and France leading to sharp rise in vulnerability becomes apparent facing European crisis only. Finally, we detect such degree of transitions for China facing the very recent 2015-16 Chinese stock market turbulence.

The Chinese market is fraught with speculations over an ensuing crisis (Forum, 2015; Mauldin, 2017; Elliott, 2017; Chiang et al., 2017; Mao, 2009). The speculations are fuelled further with the building up of 2015-16 stock market crash preceding a pronounced rise in both vulnerability and transmission. Moreover, with relatively low vulnerability and high transmission during GFC, Chinese market established exemplary resilience. This may be presumably due to China's strongly growing domestic economy and timely policy interventions contributing in the economy going upstream facing the Global Financial crisis. With the recent deterioration of Chinese resilience casting risks in Chinese stock markets within systemic risk framework requires further examining before we postulate China to be the ground zero for the next global financial crisis. There is a detailed discussion in the next chapter.

Oil Exporting Markets

Now we explore the impact of exogenous factors such as oil indices into the system by examining the changes brought about as well as for robustness in the transmission and vulnerability dynamics for both AC and EC clusters in Figure 3.6. We account for the heightened systemic risk between China and Germany leading to other EC markets in Figure 3.3 with robustness delivered in Figure 3.6. We find that oil inclusion results in systemic risk stemming more from France and the UK than others. Turning to AC markets in the other panel of the same figure, we do not find any substantial up or down swings for the AC markets with the inclusion of exogenous factor. This suggests, Asian markets have better resilience to oil shocks than other markets within a systemic risk framework.

We show the spillovers of the OED and the OEE markets (OED comprises the USA, Canada, Russia, Norway, Japan and New zealand, while OEE includes the Saudi Arabia, Israel, Iraq, Sri Lanka, Nigeria and Venezuela) in Figure 3.4. Again, we compare Figure 3.4 for robustness including oil in Figure 3.7.

We find acute swings in transmission and vulnerability for Oil Exporting Developed markets highlighted in Figure 3.4. With the exception of Japan, this holds for Venezuela,the USA, Canada, Russia and Norway.Chen et al. (2002) suggested, Venezuela is an important representative of Latin American markets. Up until 1999 there was no visible diversification in Venezuelan market due to its high level of integration with other Latin American markets. We find both Venezuelan and Russian transmissions exceed the aggregate levels during the episodes of US-led Iraq invasion; in the unveiling of GFC, throughout the European debt crisis and the recent Russian ruble Crisis. We also find that despite continuing increases in Venezuelan amplitudes, resilience in the Russian market intensifies. Additionally, Norwegian market resilience remains stronger relative to the aforementioned markets, but weaker than that of the USA and Canada.

Turning to OEE markets plotted in the second panel of Figure 3.4, we observe that since the Iraq invasion, Saudi Arabia and Israel have been the highest transmitters and recipients of return shocks, particularly in the Middle East. While only a few cycles of transmissions and vulnerabilities are discernible for Saudi Arabia and Israel during the outbreak of GFC, these pick up dramatically during the period of plunging oil prices in 2016. In the following years vulnerability increases for the Saudi Arabian markets. The remainder of the markets in OEE and OED clusters have been less resilient since the GFC with increasing systemic risk, similar to the results for the EC and GC markets.

The results for including oil shocks in these groups are presented in Figure 3.7 . We find stronger fluctuations of transmission/vulnerability for Iraq, Kuwait, the Saudi Arabia, Israel, Norway and Russia. Moreover only to Venezuela, Norwegian swings exceed that of the others in these clusters. While Norway shows heightened vulnerability to oil shocks in recent times; prior to the invasion of Iraq, Iraq's responsiveness to oil shocks were highest.

Our results support heightened fragility in energy exporting markets, heralding an increase in systemic risk. We do not find any dampening in the spillovers with the inclusion of oil shocks in Figure 3.7.

Greek Crisis

A major crisis since the Global Financial Crisis is the European debt crisis, erupting in late 2009, finding its way to major European markets. Studies in this vein suggests, the crisis spread quickly, even before policymakers became aware of the serious troubles facing the European markets (Jolly and Bradsher, 2015; Mink and De Haan, 2013; Arghyrou and Tsoukalas, 2011; Jolly and Bradsher, 2015). In figure 3.5, we present the dynamic analysis for the GC cluster. Greek, Irish, Portuguese, Croatian and Belgian systemic risk estimates continue to amplify up until 2016. The transmissions for all the markets remain high. In essence, we identify an overall upward shift in the transmissions of GC markets over the 20 years, with heightening vulnerability for Greece, UK, Ireland and Belgium in recent times.

Aiming to explain resilience in the GC markets, we point out key features in vulnerability. Vulnerability remained upstream for Greece, Portugal and Ireland up until the post European Crisis period. We detected a brief dampening in vulnerability only to be picked up much more substantially facing the smaller crises emerging in the post European crisis. The recent jump in vulnerability is the highest amplification that heralds a crisis may emanate from within the GC cluster.

The results complement Ghulam and Doering (2017) by identifying higher connectivity of GC markets to EC, OED and OEE markets. The gyrations in GC markets suggest that crisis conditions have not subsided for this cluster. The picture that emerges suggest that a larger crisis may erupt from Greece or other GC markets.

Including Oil and Commodity in Figure 6, we record amplification in overall transmission and vulnerability. This cements the robustness of our analysis while suggesting that GC markets are vulnerable to exogenous shocks to a lesser extent than that of EC, OED and OEE markets.

We again find a turning point of similar degree from dampening to magnification appearing for Belgium at the same time as Germany, Singapore, Korea and some other markets. Next we explain what causes these transitions in vulnerabilities to appear together.

Conduit effects

We detected vulnerability transitioning from dampening to amplification for Germany, Singapore, South Korea and Belgium appearing at the same time in the beginning of 2000 in Figures 3.3, 3.4, and 3.5. We aim to present rationalization for such collinear movements in vulnerability.

In Figure 3.4, we find the same turning point in the vulnerability curve appears for the USA and Japan at the same time with aforementioned markets, but to a much higher degree then others. BIS (1998) summarized that the USA and Japan were found to be conduits if not ground zero for earlier crisis events. In light of this discussion, we have detected the conduit effects of the USA and Japan to Germany, South Korea, Sri Lanka, Belgium and Australia. The crises that transpired in the USA from dot comm bubble and the subsequent energy crisis has exerted transitions from low to high vulnerability regions for Japan, South Korea, Singapore, Germany, Belgium and Australia. This may be due to high volume of trade between these markets with the USA and also with Japan at some point. In short, we have captured the conduit effects outlined in Baur and Schulze (2005).

3.5.3 Crisis Maps

We now take the DYCI spillover indices generated in the previous section as inputs to produce crisis maps in the form of Self-Organizing Maps.

Using DYCI as the raw input data rather than historic returns or financial indicators as presented in earlier papers (Marghescu et al., 2010; Sarlin and Peltonen, 2013) and Betz et al. (2014) or log prices in (Resta, 2016) we are able to provide a new way of examining systemic risks, highlighting the interconnectedness and spillovers of the system particularly in representing the paths of vulnerability in the system.

Our main contribution is to present meaningful visualizations of high dimensional inputs. The generated topology of the markets illuminate hidden overlapping and non-linear dependencies. Such technical representation is achieved by defining the topology with SOM Best Matching Units (BMU) discussed earlier.

An important novelty lies in our dynamic (windowed) mapping approach. We disaggregate our original map to thirty-nine (39) successive maps, sampling at roughly 135 rows (semi-annually) for each iteration. We extend the number of replications until all the 5041 rows are mapped. This approach allows us to visualize and examine the changing degree and direction of contagion during different crisis. What lies closest to the spirit of this paper is León et al. (2017) proposing hierarchical clustering of estimates derived from indirect networking methods.

Figure 3.9 presents the full-sample crisis map generated with SOM using unconditional spillover measures. The horizontal and vertical axes present the markets individually and in clusters. The representation is similar to a heat-map with reordered column positions. The degree of crisis is depicted with lighter to darker colors. The classifications lie between no events (when the convergence in loss function is successful) to events (when loss function is not optimally minimized for as non-linearity heightens in places). Crisis transmission is drawn along the path of events across contemporaneous market links. Additionally, the transmission pathway separates changing stress levels naturally clustered together for all data points.

We interpret the graphs as following. The darker colors represent fissures in a plateau of the mid-colors with occasional lighter colored higher features. To continue the analogy if we consider a shock as some form of flash storm somewhere in the system, then the fissures represent the path into which the storm-water will drain. Deeper fissures will attract more water. This refers to the areas that are most vulnerable. The pathways visible on the plots represent the path of least resistance for shock transmission through the system. For example, in Figure 3.9, it is clear that the markets from South Korea to Israel on the map are highly vulnerable to a shock from the US (shown on the horizontal axis). We see topographic depressions are deeper as the fissures run across GC to OED clusters. Depressions are deeper again as the crack runs through EC to AC cluster. The dislodging on the plateau forming the fissure represents the vulnerability pathway in the system carrying crisis across the system. Here, Figure 3.9 gives us a parabolic pattern in the fissures pathway that connect the major topographic depressions. Now we are presented with the question if these fissures are more ephemeral than long lasting. Figures representing dynamics in crisis maps over nearly two decades, breaks down to semi-annual time periods in Figures 3.10, 3.11, 3.12 and 3.13 to show the evolving vulnerabilities of the financial networks. In the first half of 1998, during the Asian crisis, there is a substantial web of fissures connecting many markets in the system. The vulnerability of the system to shocks is evident. This begins to ease in the second half of 1998 and into 1999. Throughout 1999 and 2000, the activity transmission loops at the right hand side of the figures are especially apparent. These maps show the high vulnerability of the OED markets, and increasingly the AC markets to shocks originating from the EC markets. Interestingly, there is little vulnerability to transmission from the US across markets either before or after the dot-com crisis (with the exception of Australia). By 2004, vulnerability to US sourced shocks evinces as a source of global vulnerability (on the left hand side of the figures) and this continues right up until early 2007. However, this does not identify the most vulnerable pathway. Instead, by 2007 markets are most vulnerable to shocks emerging from the EC countries. This possibly reflects the anticipated effects on their economies of the slowdown of the booming demand for exports due to high growth in Asia, perhaps as an indirect consequence of the reduced activity in the US following the crisis. For the following years the primary source of vulnerability in the system remains around the role of shocks from EC markets, and with shocks that affect those markets themselves (across the top of the figures).

Although we have presented how vulnerability pathway, or in other words, crisis transmission pathway in analogy to storm water mounds change along the web of fissure across the plateau, we have detected a common parabolic pattern in the fissures running from end to end throughout the plateau (the system). More coverings open up as new events are triggered and the bedrock is riddled with openings in major events, the running of storm water, drawing an analogy to crisis transmission is temporal. The new cracks fill up quickly, and the system remains with the common pattern in the pathway of crisis transmission over the entire sample period. This is a new finding presented for the first time in the vein of crisis prediction.

There are interesting small surges of vulnerability evident in hot-spots, which we denote sinkholes, in a number of the figures. According to Davis et al. (2010) and Khandani et al. (2013b), an adverse feedback loop spreads across sectors as deadly doom loop (Farhi and Tirole, 2017) and across international equity markets as diabolic loop(Brunnermeier et al., 2016) . We visualize crises spreading across different clusters in the system as a feedback loop completes circle within a cluster and find such sinkholes appearing in the system in 2004:1 for GC, 2004:2 for OED, 2006:1 and 2006:2 for AC, 2008:2 for GC, 2012:2 for EC and 2014:1 for OEE. Moreover, we find multiple sinkholes appearing in the maps for 2009:1 for GC, OED, OEE; 2010:1 for GC and OED; 2016:2 for EC. However, we are faced with the question on the importance of these sinkholes. Are these sinkholes random appearances? Can we predict crisis forming from these sinkholes?

Brunnermeier et al. (2016) suggested diabolic feedback loops transmit risks across capital markets as cascading common equities pooled in SIFIs, indicates a buildup of crisis across national borders. This in turn results in a global contagion. Turning to the first half of 2006, we detect sinkholes creeping up into the system. Can we expect that we will see crisis erupting in the following period? We see rapid dislodging on the plateau in the next period. Moving along, we show new web of deeper fissures opening up along with new sinkholes facing the GFC in 2007. Further, the parabolic pattern in the fissures pathway prevalent in calm times, is overlain with many new fissures. Crisis transmitted everywhere along the path of the common pattern. As the effect of crisis subdues, we see these new deeper fissures are filled up and the common parabolic pattern or the common fissure resumes. Again, in 2008 and in 2010 we detect unanticipated sinkholes emerging in the plateau. In both cases, the following period brings in many new openings and fissures with voids exceeding normal times leading to major crisis erupting throughout the system as heightened vulnerability is spread across the system. In the first case, we see a sudden spike in ongoing crisis, and we are faced with the European crisis in the latter case. In all cases examined, we conjecture that the openings into random sinkholes heralds imminent crisis and heightening of transmissions across the system. In the dissemination of a crisis event, the system reverts back to the common parabolic pattern. This is a new presentation in this vein of studies in terms of both long term persistence of commonality in transmission pathway and early warning system.

In contrast, we also capture strong endogenous crisis transmission in our system of dynamic mapping. For example in 2009:1 a strong vulnerability is revealed for AC markets and oil exporting emerging markets, with the sources from the USA, Australia, and India. In 2010:2 there is vulnerability for the USA and Australia from the Asian markets. This is consistent with the resilience of the Asian markets in resisting the effects of the Greek and European debt crises.

In this section we include a 10 basis crisis classification table and a 900 basis gauged from the SOM classification matrix. We generate a 0-10 degree range crisis classification in Table 3.4 and 0-900 degree range crisis classification in Table 3.5 gauging from vulnerability matrix, for each data points across rolling samples. We use a 70-30 split for test simulations based on training input. We then aggregate the classification vector into 39 subsets in compliance with the window size selection for dynamic 'crisis-maps'. We present summary statistics for each subset in Table 3.4 and Table 3.5. Table 3.5 presents the summary statistics of generated classification weights forming the dynamic crisis maps. Table 3.4 presents a simple range **showing the robustness of self organizing maps** gauging from spillover indices. In addition, both the tables demonstrate the applicability of a class of deep unsupervised learning classification on a conditional spillover index for crisis prediction.

We find high degree of stress accumulation for 1998:2, 1999:1, 1999:2, 2001:2, 2002:1, 2006:1, 2007:1, 2007:2,2008:1, 2008:2, 2009:1, 2010:2, 2011:1. Moreover, the test simulations provide accurate predictions for stress generated in 2012, 2015 and 2016. The summary statistics shown in this table complements our findings in dynamic analysis and dynamic crisis-map sections. Also the tables add to the robustness tractability and the predictability of the patterns presented in the paper.

In our DY spillover analysis, the total spillover index reached an all-time high for China. A number of papers focused on China as a potential source market (Chiang et al., 2017; Forum, 2015; Elliott, 2017; Mullen, 2017; Mauldin, 2017; Forum, 2015; Cheng, 2017). However, the full visualizations in the crisis maps do not support the conclusion that China is the source of vulnerability in the system, in fact they point more towards sensitivity to shocks from the GC and OED markets. In February 2018, this view was vindicated in the rapid transmission of shocks from the US sourced shocks to the more developed markets of the world (corresponding to significant drops in Dow Jones), reflected in the predictive patterns in the crisis maps produced for 2017:1. We present results from further investigation in this regard in the next chapter. We also provide an explanation on why a crisis transpiring from China is contained.

What follows next is complete counterfactual analysis results for dynamic spillover section and for the crisis maps.

3.6 Counterfactual analysis

3.6.1 Counterfactual conditional spillovers

Counterfactuals invoke causal relations alternative to the existing association by modifying past inputs. However, without access to controlled experimental conditions true counterfactuals are almost impossible to perform in the literature. While critiques of counterfactuals postulate that altering causal relations may generate erroneous results (Dawid, 2000), the advocates of counterfactual analysis provide evidence of its usefulness, in that, results drawn from alternatives may help actions to mitigate undesirable consequences from crisis conditions elsewhere in the network (Pearl, 2000, 2002). We present counterfactual experiment results in this light.

We execute our counterfactual experiments by constraining selected effects in transmission process, specifically by constraining a number of the largest identified bi-variate pairwise linkages to zero. In policy terms we link this to a policy intervention designed to halt transmission between two nodes.

The *first counterfactual* considers the case where all the large links either receiving or transmitting identified as being over 100 basis points are set to zero. We then re-estimate the spillover indices with those links set to zero and all other link values from the original VAR retained.

We begin by presenting counterfactual dynamic conditional spillovers that marks crucial changes with counterfactuals in Figure 3.14 and in Figure 3.15. Not all counterfactual estimates capture substantial deviation from findings in non-counterfactuals.

We find transmissions around global financial crisis only amplifies for Australia, Israel, Japan, South Korea and New Zealand when these market's links with Germany is turned off. The transmissions for these market's exceed that of with all existing links. Interestingly, the American transmissions spike up only when its link with New Zealand is turned off. Seemingly, cutting links off, specifically with Germany, heightens risk transmissions for all markets.

We focus on interesting findings with vulnerability spillovers when we turn individual pairwise links off. We show that the entire Japanese vulnerability curve shifts down, or in other words, Japanese market becomes stronger as we turn its link off with the USA. Similarly, we show that Malaysian market becomes stronger when we cut its link off with the USA. Put together, it is an interesting finding to see that strong links with the USA market increases crisis related vulnerability for several countries that are the closest trade partners to the USA as well. We do not extract similar deviations neither in vulnerability nor in transmission by conditioning on any other associations.

Moreover, two notable findings are presented here. We identify that the overall transmission and vulnerability for Australia amplifies for the entire cycles if Australian links to both the USA and Germany is turned off. Also, We find the USA vulnerability increasing substantially only when the links to New Zealand is turned off. It is evident from the results that the USA market interdependence to New Zealand is stronger then others in the cluster. This significant interdependence for both markets maybe attributable to the phenomenal alternative investments between the USA and New Zealand as major energy exporters in the same cluster.

The findings in Figure 3.14 and in Figure 3.14 supports our argument that limiting exposure to certain markets may exacerbate systemic risks for others while serving as the dynamic robustness of the unconditional connectedness presented in the dynamic analysis section of the paper.

3.6.2 Crisis-maps

Now we set two conditions in counterfactuals. In *counterfactual one* we turn all big links off altogether to re-examine changes in transmission pathways in crisis-maps. Then, in *counterfactual two* we turn individual pairwise associations off for all markets as before (In the spirit of capturing shocks received by home country, we only present maps with Germany-Australia links off here. However, maps with all other links off, or any specific links off can be produces and supplied upon request). These serves the purpose of explaining, if controlling for all big transmissions substantially changes the transmission pathways while allowing us the flexibility to examine changes in fissures with individual associations. Consequently, this either yields new information or proves robustness in the visualizations.

We present full-sample crisis map generated with *counterfactual one* in Figure 3.16 and with *counterfactual two* in Figure 3.17.

The picture that emerges from examining the full sample maps with the first restrictions applied, is the fissures running left to right in Figure 3.16 replicates the pattern of fissures produced with all links existing as found in Figure 3.9 the main body of the paper, but with voids deeper then Figure 3.14, carrying more storm water deposits (higher degree of shocks) within them. This demonstrates that controlling for big transmissions, the parabolic pattern in the transmission pathway is not hindered. Additionally, the figures suggest that with *counterfactual one* severity of crisis intensifies while makes evident the robustness of earlier crisis maps.

In contrast, Figure 3.17 lays out full sample map and Figure 3.18 lays out the dynamic sample maps with only Germany-Australia links off. It is clear that the plateau is riddled with openings into deeper voids, and with new cracks emerging within the parabolic pattern running from Germany to OED cluster, through the GC cluster. This illustrates that with one major link off triggers crisis spreading all over. This only reinforces the argument that we need to be cautious in selecting what links to turn off if we want to short circuit an imminent crisis instead of exacerbating it.

We conclude that even if we shut off big links all together we retain some degree of persistence in the patterns and the patterns remain predictable. Shutting off random links only results in lose control over the patterns.

3.6.3 Policy Implications

One of the most appealing features of the crisis maps is that they are able to display the changing nature of vulnerabilities within a financial system in a readily accessible manner. Despite the usefulness and wide range of applications for the DY adjacency matrix approach, complementary information can be obtained from crisis maps in terms of both the amplification of spillovers and the emergence of specific areas of vulnerability.

The rolling spillover indices and the crisis maps both show that the system can move dramatically. Consequently, the range of tools required by policy makers and portfolio managers needs to be wide. In some instances shutting down a link between two markets may protect other markets, but the results of our counterfactuals suggest that the effects on the overall crisis map are not easily detected.Diagonal fissure lines across the system result from cascades of shocks sourced at an origin market and traveling on via the fissures in the system (e.g., US to Australia to Japan). The crisis maps highlight both the direct and indirect nature of these relationships and as such co-ordinated actions may be an appropriate means to short-circuit a crisis. For example, by blocking a pathway, perhaps through policy options such as short sales constraints, or short-term capital movement restrictions.

In other cases sink-holes emerge. These are hot spots where there is a high level of vulnerability for an individual market (or small number of markets) to shocks from a single source (or small set of sources). In this case an apt policy response may be to develop a domestic response to the cause of that vulnerability - possibly involving the traditional repair of macroeconomic fundamentals such as proposed in first generation crisis models; see, for example Eichengreen et al. (1996); Eichengreen and Hausmann (1999); Bordo et al. (2001). Alternatively the cause may be vulnerability to structural issues such as high reliance on remittances.

3.7 Conclusion

In this paper we present return spillover connectedness between major global markets split into multiple categories based on their size, structure and roles played during major financial crises periods. First, we make use of unconditional spillover measures to analyze static networks of markets, and conditional spillover measures to analyze changing interaction of dynamics between major markets. Our analysis not only captures the degree and direction of the episodes affecting 31 international equity markets in the past 20 years, but also allows us to explain how the strengthening of networks are responsible for uncertainties.

This paper proposes a unique way of visualizing the changing vulnerability of a financial network via automated neural networks (ANN), and by filtering on the largest vulnerabilities provides crisis maps. These crisis maps highlight the least resistance shock transmission pathways at any point in time. We show how ANN methods relate to the commonly understood VAR representation and hence can be cast as an extension of the Diebold and Yilmaz (2009); Diebold and Yılmaz (2014) approach.

Time shots provide 'crisis-maps' that detect the changes in vulnerability for markets over time. Not only do we present a complete 'crisis-map' showing a conceptual pathway for shock transmission, but we also give time varying patterns by presenting step-wise windowed stress grids.

We investigate several issues that are central to scientific discourse in the systemic risk tenet of studies. First, we provide evidence of timely intervention leading to reduction of vulnerability for many markets in the past. Second, our results reflect that changing interaction between markets are inducing transmissions that were considered vulnerable in the past, while postulated risky markets are not transmitting risks.

Third, we demonstrate that AC cluster is more resilient then before. Fourth, we conjecture that cutting links off may increase resilience for some countries in some scenarios. In so doing, the aberrations caused in the system instigates larger and quicker crisis transmission in most simulations. Fifth, we account for a common and persistent pattern in the pathway of shock transmission that is only disrupted with the eruption of strong crises. Finally, we propose a robust way of crisis prediction serving as early warning of crisis. Taken together, these results confirm that the countries in a system alone cannot slip out of an imminent crisis. Crucially, all countries in a system need to come together in order to short-circuit an emerging crisis.

The 'crisis-maps' highlight both the vulnerability and resilience dynamics in the markets examined. With an eye to practical applications, the maps presents an opportunity for investors and financial managers to diversify wealth better, enabling them to predict riskiness patterns in their portfolios. Additionally, our dynamic mapping method of channels of potential vulnerability enables policymakers to adopt proactive measures. Despite arguably underestimating the importance of interconnectedness in the pre-GFC period, policymakers have since realized the importance of identifying and co-ordinating their responses to vulnerability to crises originating elsewhere (León et al., 2017). The patterns observed in the crisis map are a means of visualising vulnerability to policymakers, who may then base their decisions regarding actions towards channels which might be worth restricting or encouraging, to protect individual markets from unfavourable shocks. These tools may help to capture the complexity of the changing nature of integration of world markets.

Our aim is to convincingly implement means by which crisis mangers can simulate the effect of alternative intervention paths in a network and have some knowledge of where the most effective interventions may lie given the structure of the network at any point in time. Thus, we specifically acknowledge the conditional nature of the problem, and that intervention strategies may need to be flexible and time-varying, responding to the changing structure of the network and the many alternative possible sources of shocks.

In the next chapter, we investigate if a novel conditional variance spillover index compared to the DY spillover index can detect contagious markets better. We aim to examine if the a novel identification approach can sufficiently capture all events compared to DY spillover index. Moreover, we also try and explain why highly speculated Chinese risk amplifications is not leading to a full scale global crisis. The next chapter expands upon the findings presented here.

3.8 Figures & Tables

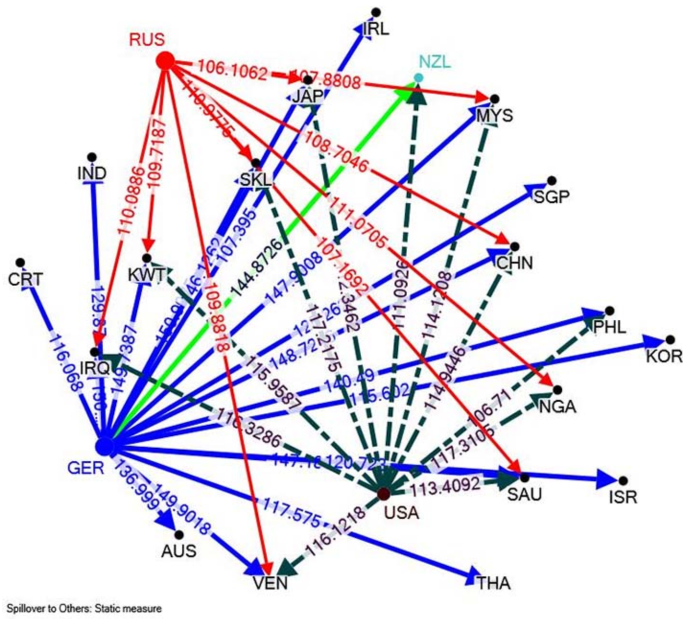


Figure 3.1: Static network- major contributors

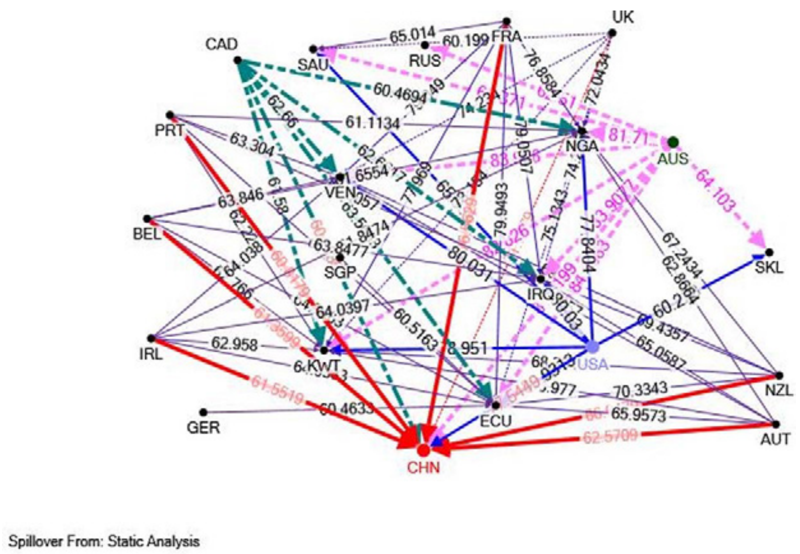


Figure 3.2: Static network- major receivers

Note: Edge arrow size indicate directional connectedness To others. The weights of networks are labeled on the edges. Here, the vertexes are filtered out based on weights between 100-150 percentile point. The maximum edge weight is 150 percentile point.

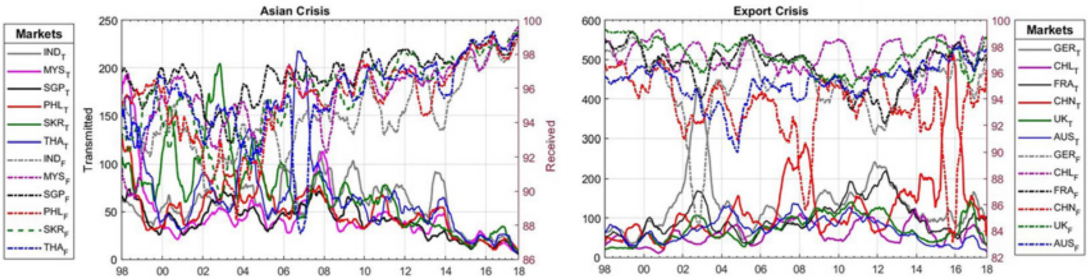


Figure 3.3: Asian crisis markets & export crisis markets.
Note: This figure represents a contemporaneous relationship of daily return data for 20 years, for markets categorized within Asian crisis (AC) and export crisis (EC) markets derived from generalized variance decomposition. A detailed description can be found in the 'Asian crisis' and the 'Export crisis' subsections under Dynamic Analysis.

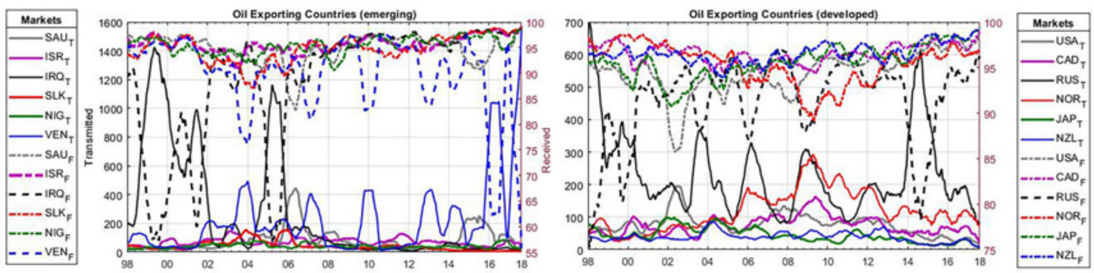


Figure 3.4: Oil exporting (emerging) markets & oil exporting (developed) Mmrkets.
Note: This figure represents a contemporaneous relationship of daily return data for 20 years, for markets clustered within Emerging Oil exporting countries (OEE) and developed oil exporting countries (OED). A detailed description can be found in the 'Oil Exporting markets' and 'Conduit effects' subsections under Dynamic Analysis.

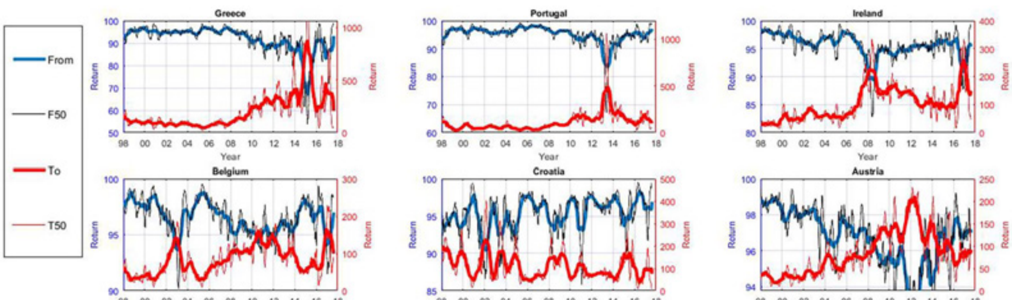


Figure 3.5: Greek crisis markets.
Note:This figure represents a contemporaneous relationship of daily return data for 20 years, for sample markets of Greece, Portugal, Ireland, Belgium, Croatia and Austria. A detailed description can be found in 'Greek Crisis' subsection under Dynamic Analysis.

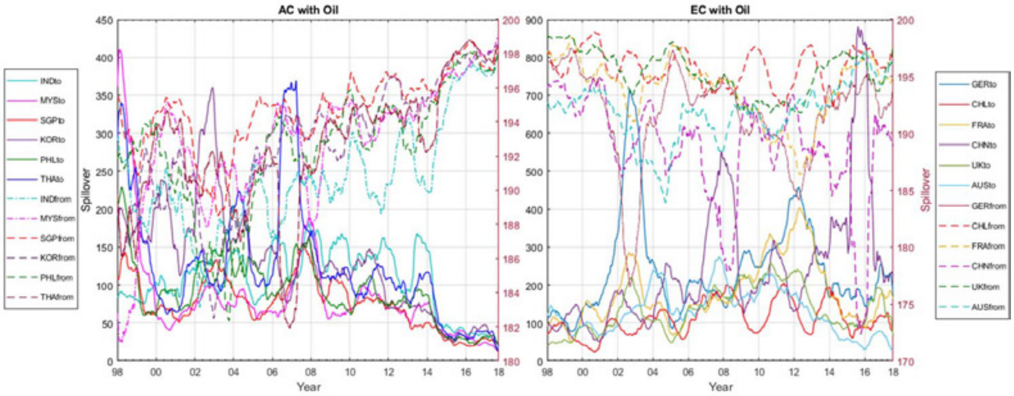


Figure 3.6: AC-EC spillovers [oil effect]

This figure represents the conditional spillovers with oil index as exogenous to AC and EC blocks. A detailed description can be found in 'Oil Exporting markets' subsection under Dynamic Analysis.

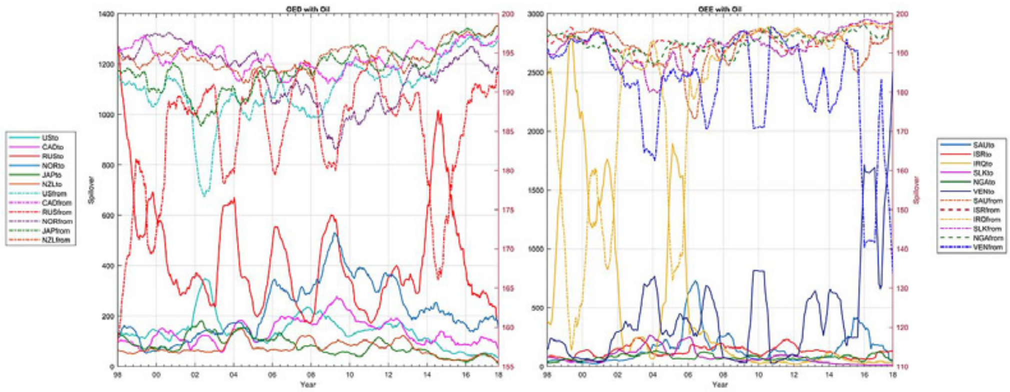


Figure 3.7: OED-OEE spillovers with [oil effect]

This figure represents the conditional spillovers with oil index as exogenous to OED and OEE blocks. A detailed description can be found in 'Oil Exporting markets' subsection under Dynamic Analysis.

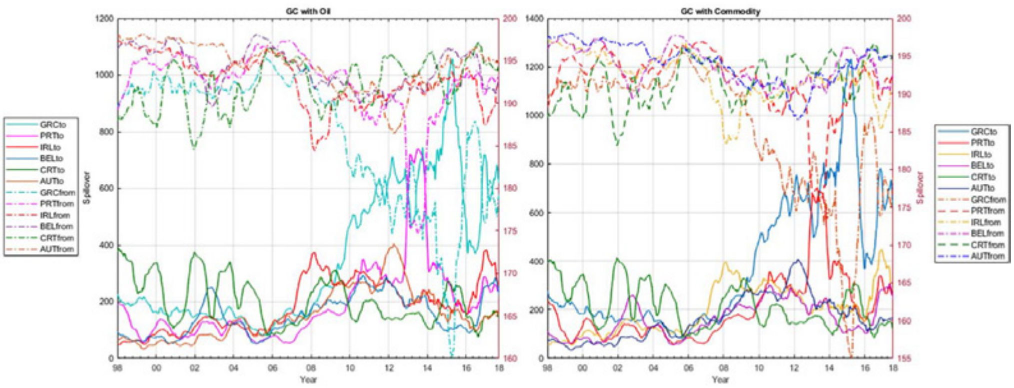


Figure 3.8: GC spillovers [Oil and commodity effect]

This figure represent the conditional spillovers with oil and commodity index as exogenous to the sample blocks. A detailed description can be found in 'Greek Crisis' subsection under Dynamic Analysis.

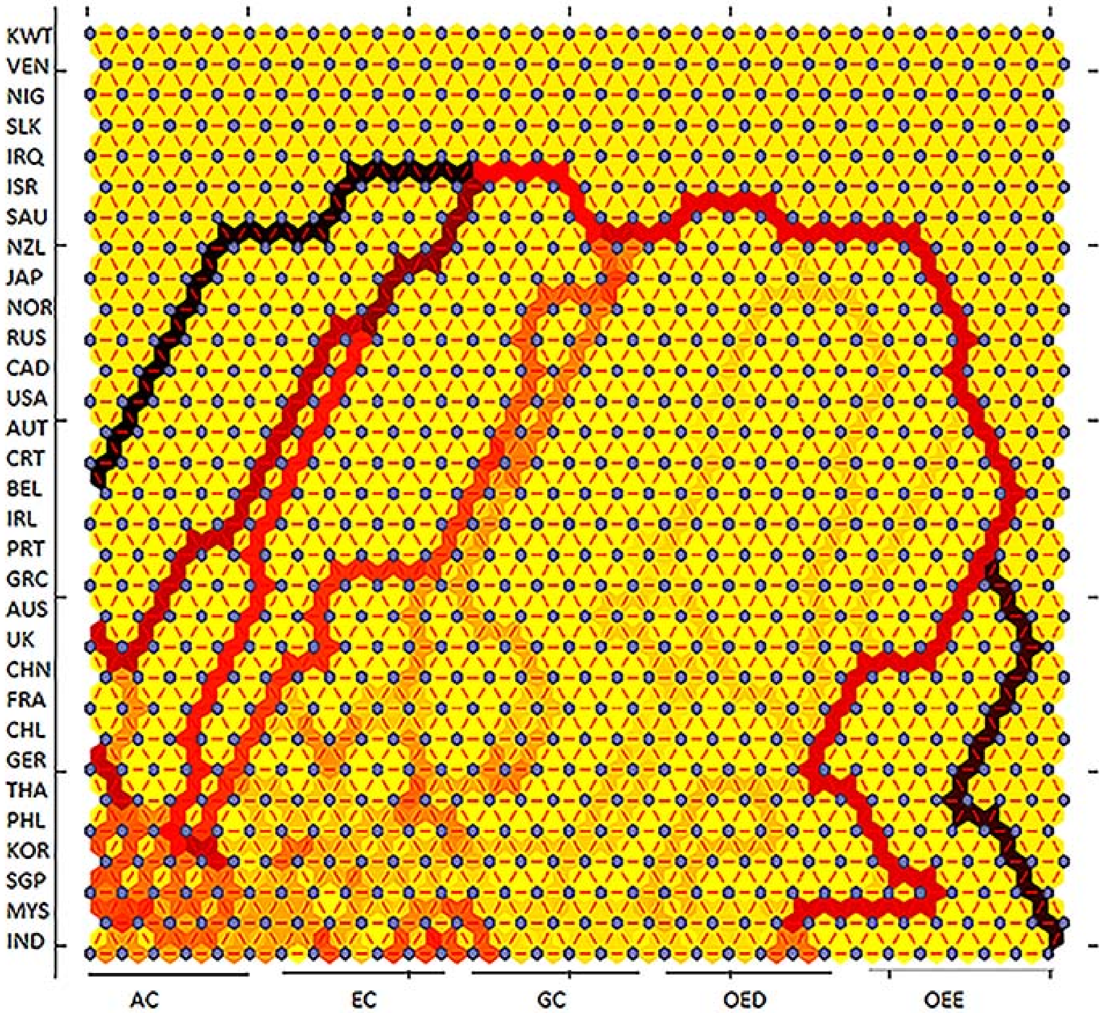
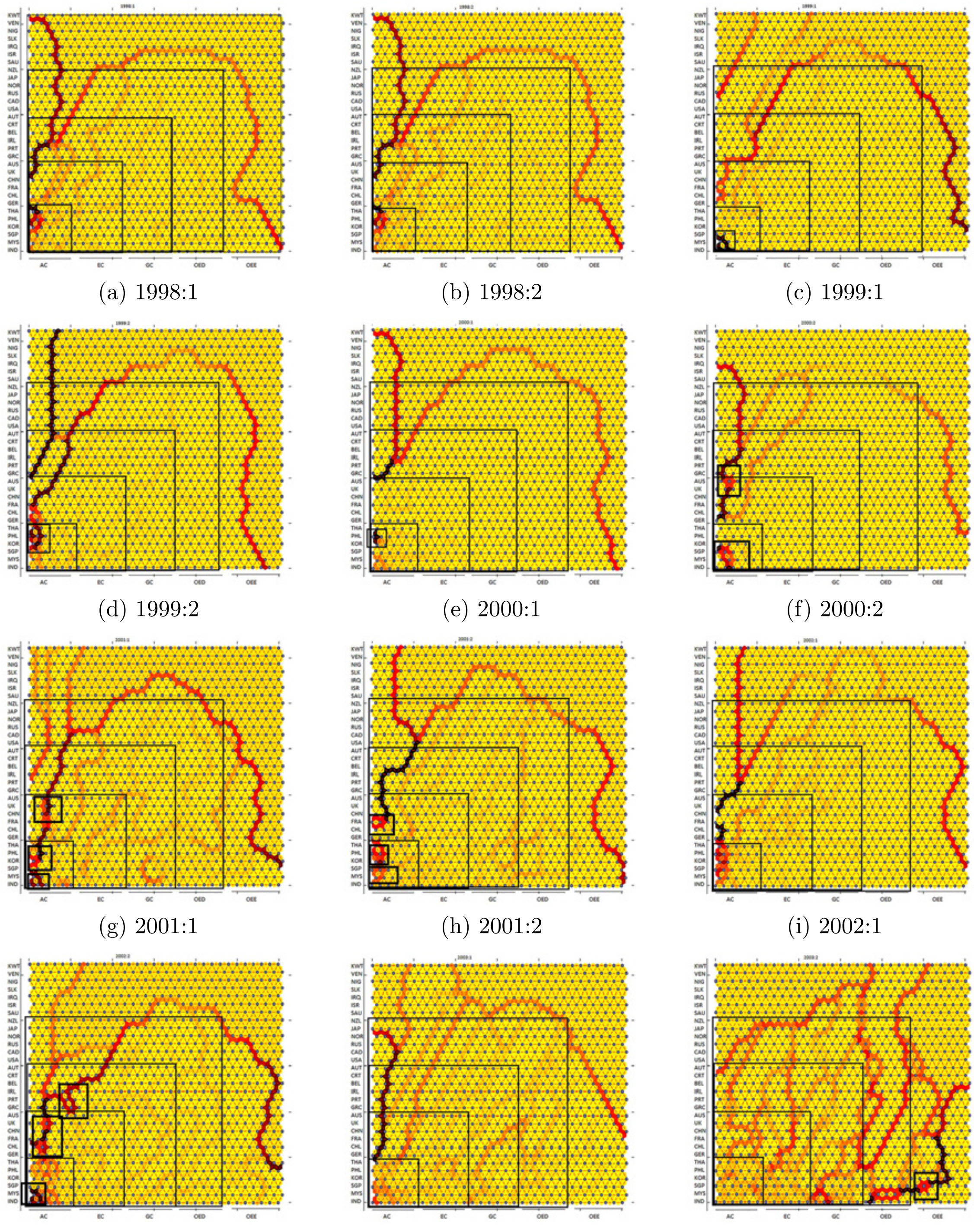


Figure 3.9: Crisis-Map (full sample period): Maps generated with SOM gauging raw data from DY unconditional spillover transmission measures with 70-30 splits on the full sample period for all vectors. A detailed description is outlined in 'Crisis Maps' section.



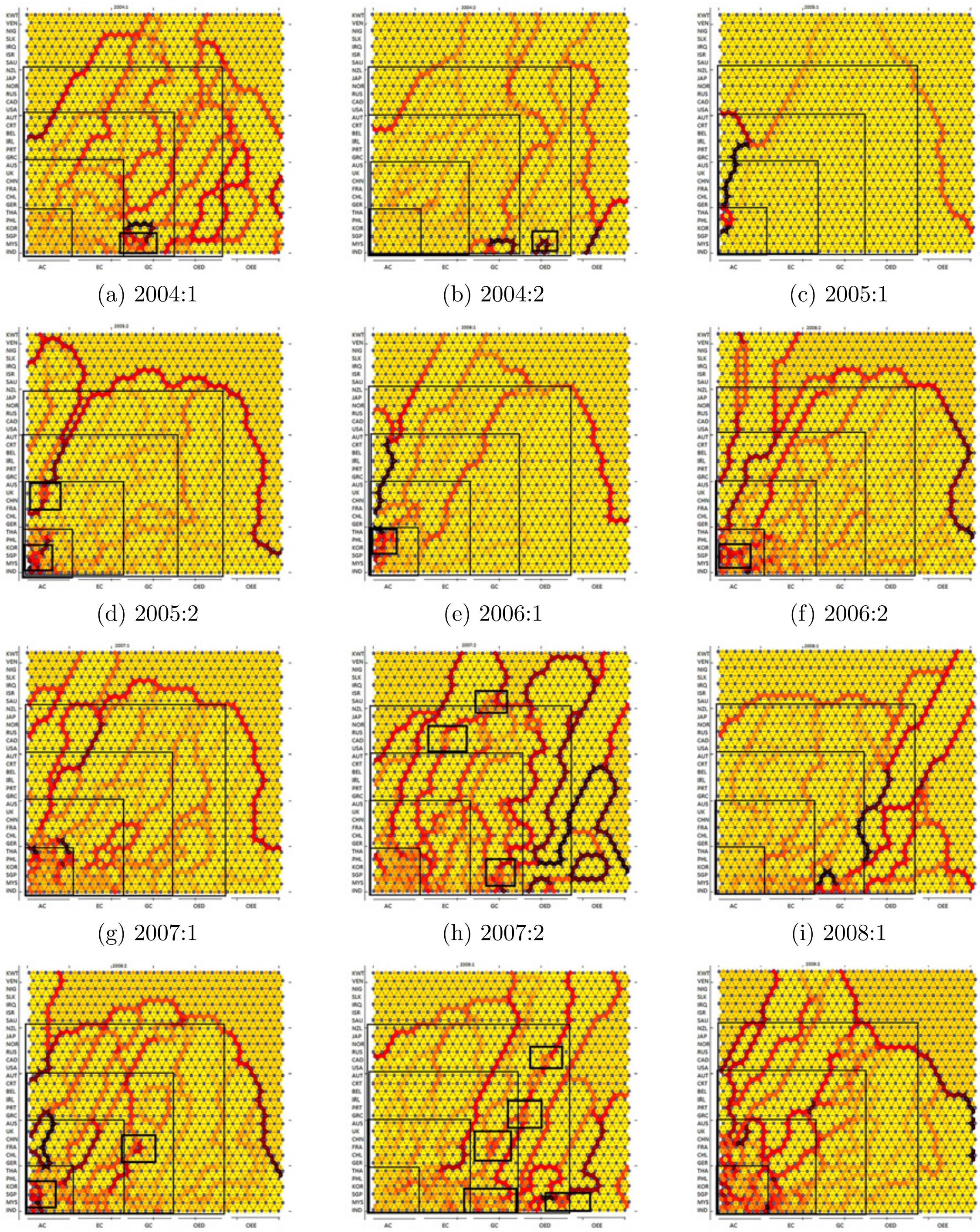
(a) 1998:1 (b) 1998:2 (c) 1999:1

(d) 1999:2 (e) 2000:1 (f) 2000:2

(g) 2001:1 (h) 2001:2 (i) 2002:1

(j) 2002:2 (k) 2003:1 (l) 2003:2

Figure 3.10: Dynamic crisis transmission maps from 1998-2003. Maps generated with SOM gauging raw data from DYCI transmission with 70-30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.



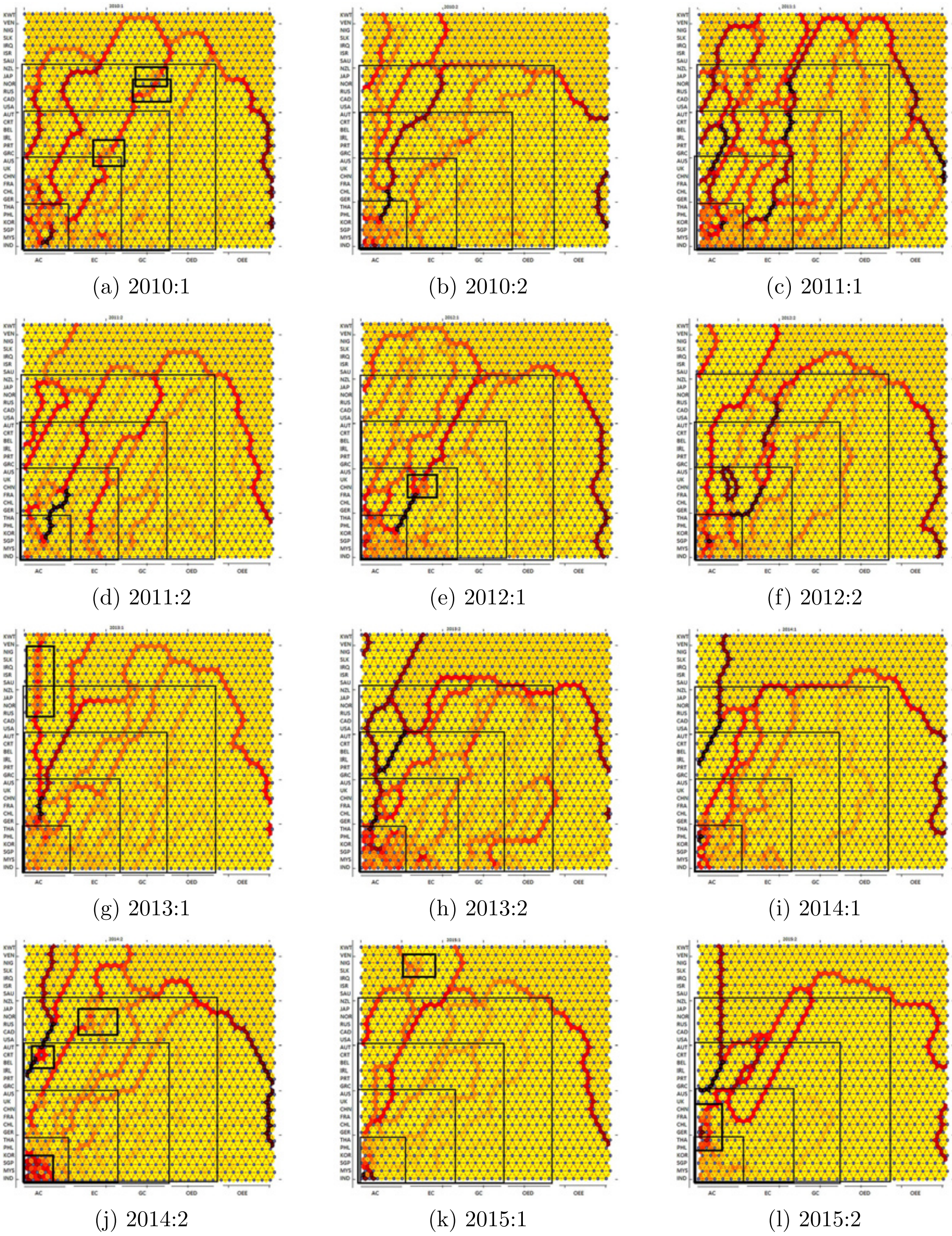
(a) 2004:1 (b) 2004:2 (c) 2005:1

(d) 2005:2 (e) 2006:1 (f) 2006:2

(g) 2007:1 (h) 2007:2 (i) 2008:1

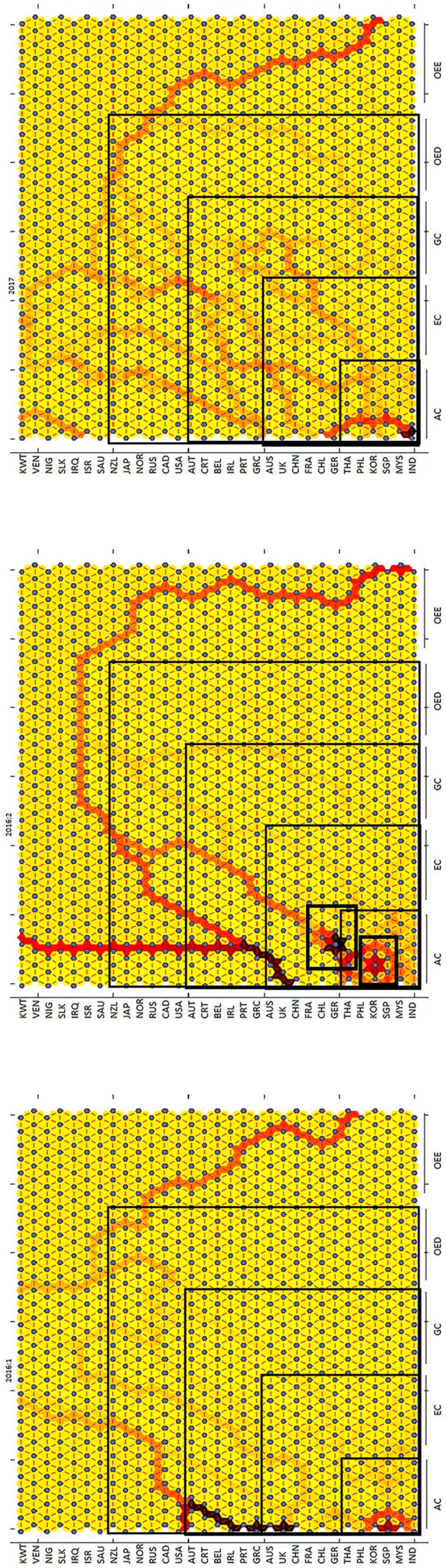
(j) 2008:2 (k) 2009:1 (l) 2009:2

Figure 3.11: Dynamic crisis transmission maps from 2004-2009. Maps generated with SOM gauging raw data from DYCI transmission with 70-30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.



(a) 2010:1
(b) 2010:2
(c) 2011:1
(d) 2011:2
(e) 2012:1
(f) 2012:2
(g) 2013:1
(h) 2013:2
(i) 2014:1
(j) 2014:2
(k) 2015:1
(l) 2015:2

Figure 3.12: Dynamic crisis transmission maps from 2010-2015. Maps generated with SOM gauging raw data from DYCI transmission with 70-30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.

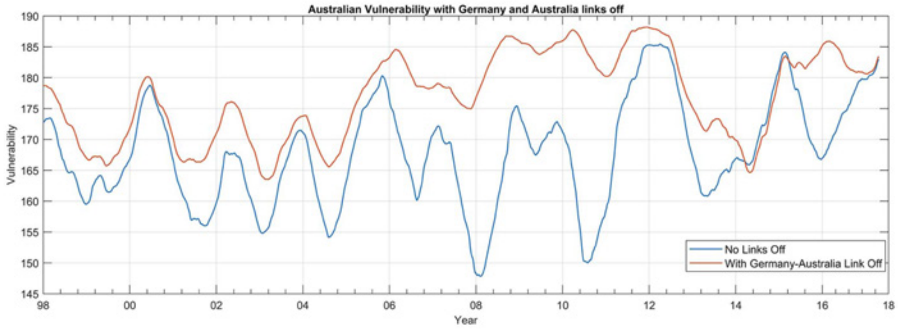


(a) 2016:1

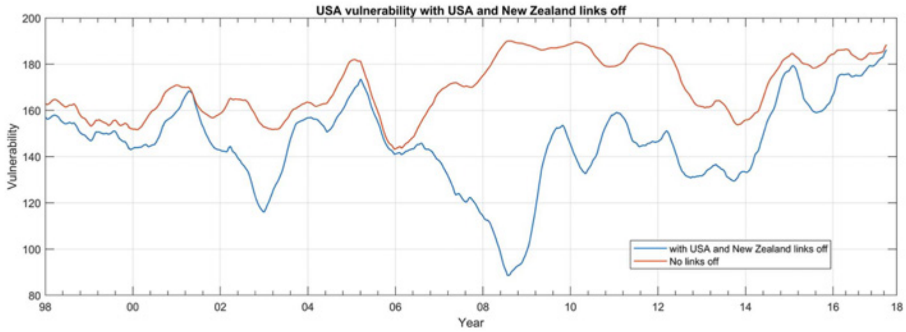
(b) 2016:2

(c) 2017:1

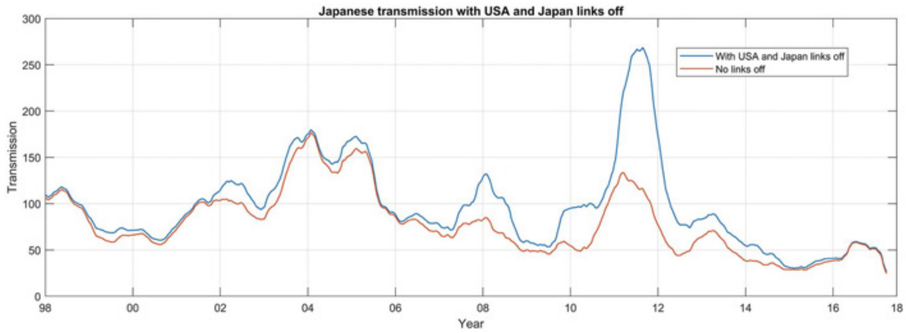
Figure 3.13: Dynamic crisis transmission maps from 2016-2017(Crisis Prediction). Maps generated with SOM gauging raw data from DYCI transmission with 70-30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.



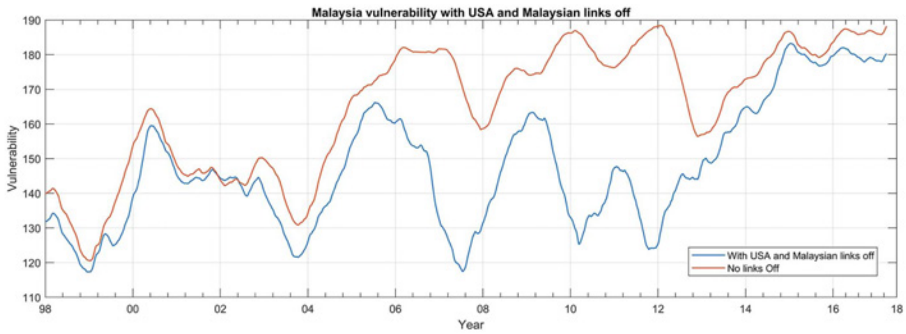
(a) Australian vulnerability:GER-AUS links off



(b) USA vulnerability:USA-NZL links off



(c) JAP vulnerability:USA-JAP links off



(d) MYS vulnerability:USA-MYS links off

Figure 3.14: Highest variations with individual links off. The figures present counterfactual conditional spillover measures, by turning specific connections off.

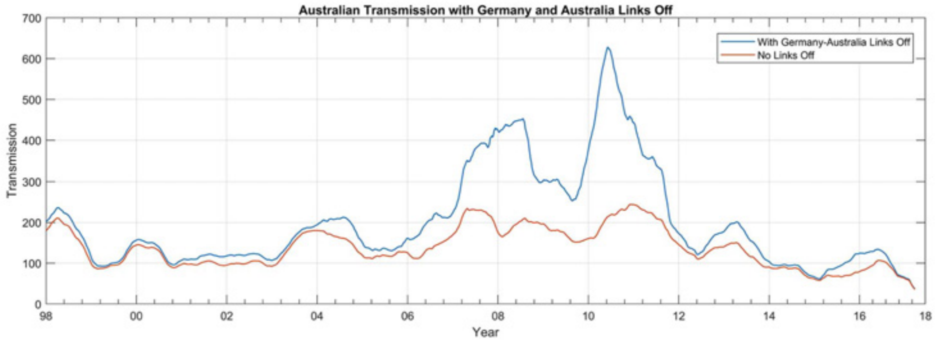


Figure 3.15: Australian transmission with GER-AUS individual links off. The figure presents counterfactual conditional spillover measures, by turning off return shocks coming to Australia from Germany.

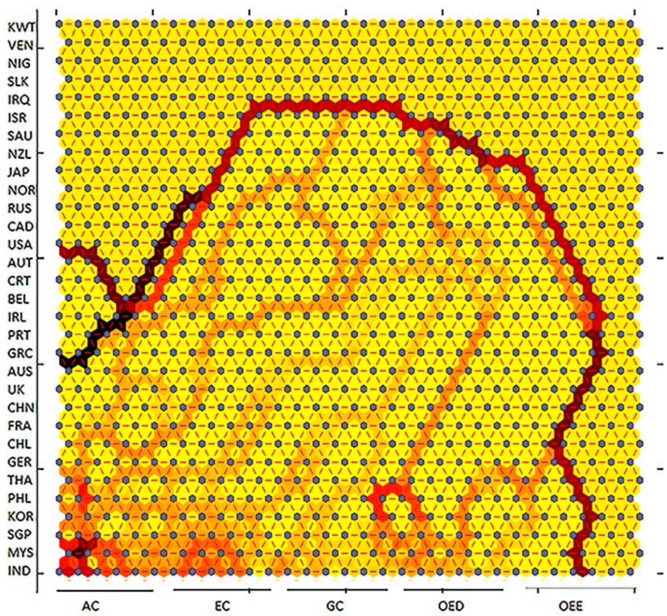


Figure 3.16: Counter-factual full sample crisis map. This figure represents a full sample crisis-map for the complete period with all big links off from bi-variate pairwise 'TO' estimates

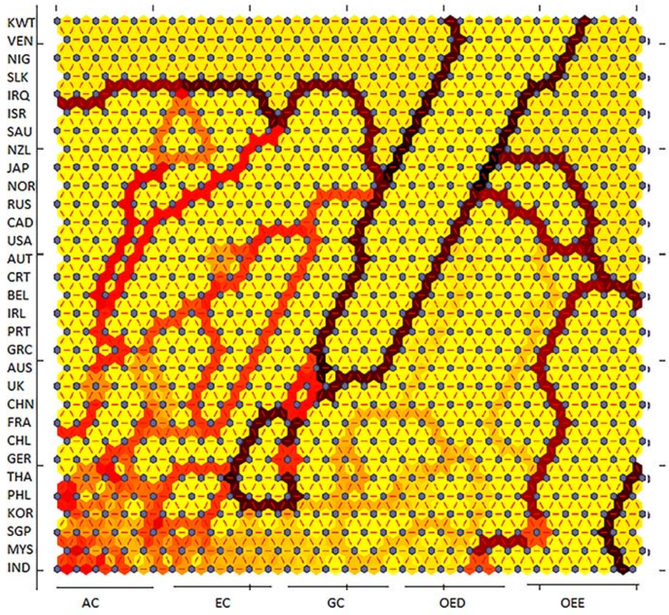
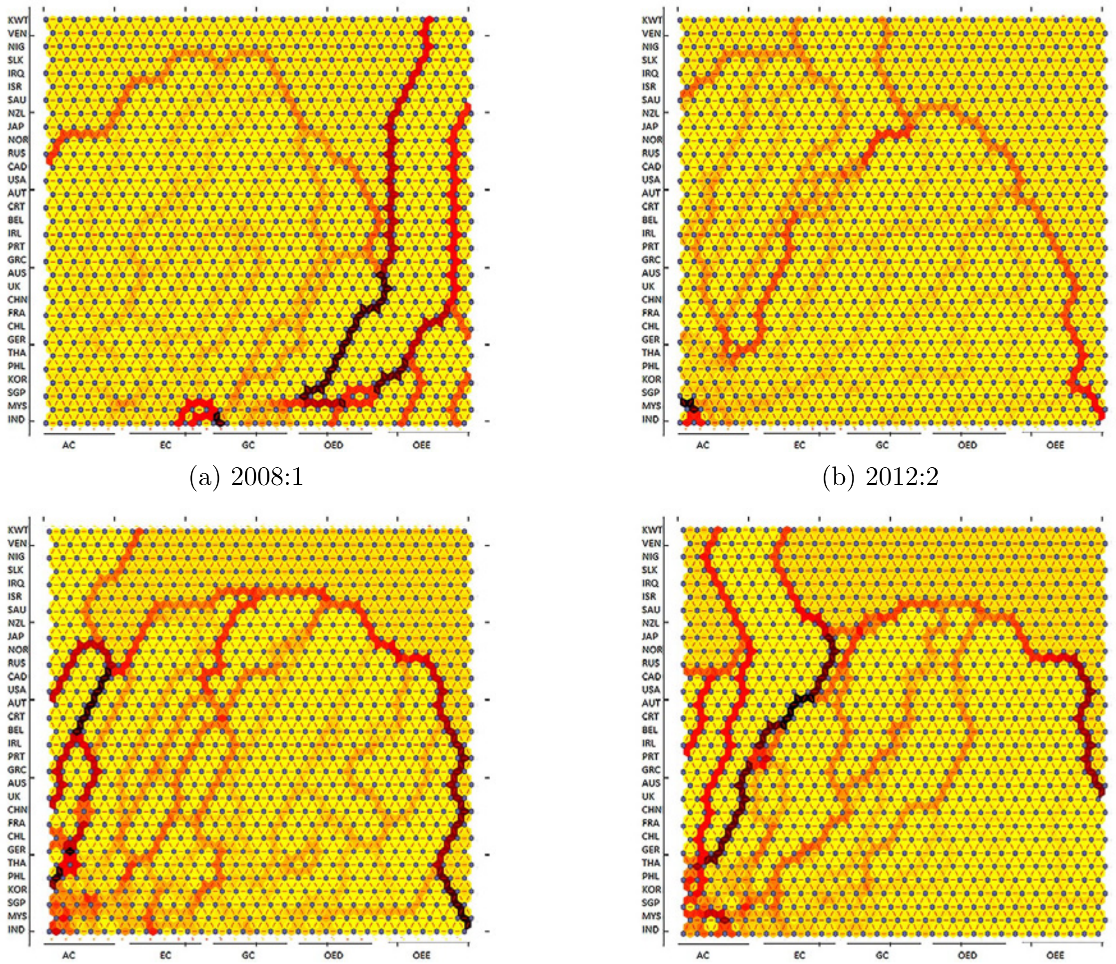


Figure 3.17: Counter-factual full sample crisis map with only Germany -Australia link off. This figure represents a full sample crisis-map for the complete period with Germany - Australia links off from bi-variate pairwise 'TO' estimates



(a) 2008:1

(b) 2012:2

(c) 2008:1

(d) 2012:2

Figure 3.18: Change in global crisis transmission controlling for Australia and Germany link, compared to controlling for all links in the post GFC and EC period

Table 3.1: Countries by analytical group

Exporters	Commodity Exporters	Oil Exporters	Greek Crisis	Asian Crisis	Conduit Countries
EC	CE	OE	GRC	AC	CC
Australia	Australia	Canada	Austria	Australia	Japan
China	Canada	Ecuador	Belgium	China	USA
Chile	France	Iraq	Croatia	India	
Germany	Japan	Israel	Greece	Malaysia	
Nigeria	New Zealand	Kuwait	Ireland	Philippines	
Norway	UK	Nigeria	Portugal	Singapore	
Russia		Saudi Arabia		South Korea	
Saudi Arabia		Venezuela		Sri Lanka	
South Korea		USA		Thailand	

Table 3.2: Major crisis events. We analyze all events across entire sample period with DY rolling estimates.

Modelling crisis : We summarize important edges found in all conditional spillover figures.			
Year	Transmission- Markets	Vulnerability-markets	Crisis events
1998:1	Malaysia, The Phillipines, Croatia, Russia, Japan	Greece, , Portugal, Ireland, Austria, USA, Japan, Venezuela	**1**. 1997 Asian Financial Crisis continues. **2**. Sourcing from the collapse of Thai baht, resulting in Thailand becoming effectively bankrupt.
1998:2	Malaysia, India, The Philippines, Singapore, Australia, Chili, Norway	Malaysia, Greece, , Portugal, Ireland, Belgium, Croatia, Austria, Japan, Venezuela	**1**. 1998 Russian Financial crisis- Devaluation of the ruble followed by Russian Central Bank defaulting on its debt **2**. 1998 Oil price crash follows
1999:1		Malaysia, The Phillipines, Singapore, South Korea, Greece, , Portugal, Ireland, Croatia, Austria, Canada, Russia, Norway, Japan, Iraq, Sri Lanka, Nigeria, Venezuela	Ecuador financial crisis followed by Brazilian Financial crisis and South American economic crisis, effecting many of the GC countries and spreading through the oil markets into Oil dependent countries.
1999:2	USA, Russia, Iraq, Nigeria	Malaysia, The Phillipines, South Korea, Germany, France, Greece, Portugal, Ireland, Austria, Saudi Arabia, Nigeria, Venezuela	1998-1999 Russian Financial Crisis continues.
2000:1	India, South Korea, UK, France, Australia, Croatia, Canada, New Zealand, Israel	Malaysia, The Phillipines, Greece, Portugal, Ireland, Belgium, Croatia, Austria, Saudi Arabia, Israel, Venezuela	**1**. Early 2000s recession effecting Euroopean Union , the USA (commencing). **2**. Japan's 1990s recession (the lost decade) continues.
2000:2		Malaysia, Singapore, Chili, Greece, Portugal, Ireland, Austria, Russia, Saudi Arabia, Venezuela	The dot com bubble leading to dot comm stock market crash, effecting the USA and Canada mostly.
2001:1		Singapore, South Korea, China, Greece, Portugal, Ireland, Austria,USA, Canada, Russia, New Zealand, Saudi Arabia, Iraq, Sri Lanka, Nigeria	The dot com crash continues.
2001:2	Chili, Japan, Iraq, Nigeria	Greece, Portugal, Ireland, Austria, Canada, Russia, Japan, Venezuela	**1**. Early 2000s recession continues. **2**. Japan's 1990s recession (the lost decade) continues.
2002:1	India, Croatia,Japan, Sri Lanka, Nigeria	Greece, Portugal, Ireland, Austria, Russia, Iraq	**1**. The dot com crash continue.s **2**. Japan's 1990s recession (the lost decade) continues.
2002:2	South Korea, Belgium,USA, Canada	India, Chili, Greece, Portugal, Ireland, Croatia, Austria, Russia	**1**. US Stock marker crash in 2002 followed by excessive speculations prevalent in 1997-2000 led from the September 2011 terrorist attack on US. **2**. Enron bankruptcy , Tyco and Worldcom scandals effected energy stocks around the globe emerging from the USA .

continue on the next page

Table 3.2: Major crisis events

Modelling crisis			
Year	Transmission- Markets	Vulnerability-markets	Crisis events
2003:1	Singapore, South Korea, Germany, UK, France, Croatia, Saudi Arabia	India, Greece, Portugal, Ireland, Austria, Canada, Russia	**1**. The dot com crash continues. **2**. Japan's 1990s recession continues.
2003:2	The Philippines, Singapore, Russia, Sri Lanka	India, China, Greece, Portugal, Ireland, Iraq, Nigeria	**1**. Global energy crisis- Increasing tensions in Middle East together with rising concerns over oil price speculations followed by a significant fall of US dollar , resulted in oil prices rise abruptly, exceeding three times the price at the beginning. **2**. SARS outbreak : First identified in Guangdong province in China, rapidly took an epidemic form worldwide, slowing down economic interactions with China to many markets.
2004:1	The Philippines, Australia, Chili,USA, Canada, New Zealand, Nigeria, Venezuela	India, South Korea,Greece, Portugal, Ireland, Croatia,USA, Japan, Israel, Venezuela.	**1**. Global energy crisis continues. **2**. The dot com crisis continues. **3**. Japan's 1990s recession continues.
2004:2	Croatia, Japan	Greece, Portugal, Ireland, Venezuela	Petrocurrency effect subdues
2005:1	South Korea, China, Iraq	Singapore, Germany, France, Greece, Portugal, Ireland, Belgium, Canada, Russia, Japan, New Zealand, Sri Lanka, Nigeria, Venezuela	**1**. Global energy market starts to recover. **2**. With petrocurrency effect subsiding, this period sees a buoyant global stock markets.
2005:2		Singapore, South Korea, Germany, Australia, Chili, Greece, Portugal, Ireland, Croatia, Canada, Venezuela	
2006:1	South Korea, Russia, Norway,Japan, Saudi Arabia, Saudi Arabia, Sri Lanka	Singapore, Greece, Portugal,USA, Iraq, Venezuela	The GAZA conflict emerges, amplifying the energy crisis.
2006:2	India, UK, Canada, Nigeria	The Philippines , South Korea, Greece, Portugal, Japan	
2007:1		India, The Philippines, South Korea, Greece, Portugal, Canada, Japan, Saudi Arabia, Israel, Sri Lanka, Nigeria	Global Financial Crisis (GFC) emerges
2007:2	Thailand, The Philippines, India, The Singapore, South Korea, UK, Australia, Chili, Ireland,USA, Canada, New Zealand, Saudi Arabia, Israel, Venezuela	Thailand, Greece, Portugal, Canada, Russia, Norway, New Zealand	
2008:1	China, Chili, Ireland, Belgium, Saudi Arabia		**1**. The Global financial crisis continues. **2**. Post 2008 Irish banking crisis ensues.
2008:2	India, Croatia	Singapore, Thailand, Australia	

continue on the next page

Table 3.2: Major crisis events

Modelling crisis			
Year	Transmission- Markets	Vulnerability-markets	Crisis events
2009:1	Croatia, Austria, Canada, Russia, Norway, New Zealand, Israel, Venezuela	China, Australia, Ireland, Belgium, Japan, Saudi Arabia, Sri Lanka, Venezuela	**1**. 2008 -2011 Icelandic financial crisis leads to credit crisis in UK, hurting the euro-zone areas to some extent. **2**. Russian crisis: the great recession in Russia begins resulting in a full fledged economic crisis in Russia. **3**. Spanish financial crisis/ Great Spanish depression begins. **4**. Eurozone crisis/ Greek crisis: In the wake of Great recession in the late 2009 , several Eurozone members (Greece, Portugal, Ireland, Spain, Cyprus) failed to bailout over-indebted banks and repay foreign debt. 2009-2010 Venezuelan banking crisis unearths.
2009:2	India, Singapore, Germany, UK, Nigeria	China, Chili, Norway	The post 2008 Irish banking crisis leaves German and French banks exposed , having enormous foreign claims in Greece, Ireland, Portugal, Italy, Spain (Greek crisis countries).
2010:1	Belgium	India, The Philippines, Croatia,USA, Canada, Japan, New Zealand, Israel, Nigeria	
2010:2	UK, France, Australia, Portugal, Croatia	The Philippines, Singapore, Venezuela	**1**. Eurozone crisis/ Greek crisis deepens. **2**. Spanish financial crisis/ Great Spanish depression further fuels in the European sovereign debt crisis. **3**. Venezuelan banking crisis continues. **4**. Spanish financial crisis/ Great Spanish depression continues.
2011:1	The Philippines, Portugal, Japan, New-Zealand	Russia, Norway, Sri Lanka, Venezuela	**1**. Eurozone crisis heightens. **2**. Great Spanish depression contributes in the worsening of Eurozone crisis.
2011:2	India, Belgium, USA, Saudi Arabia, Israel	China, Croatia, New Zealand, Venezuela	Heightening Eurozone crisis, Spanish crisis, Venezuelan crisis reinforces feedback loops across global financial markets, recoupling emerging energy dependent and oil exporting country's markets. This in turn, reinforces risk transmissions back into the USA.

continue on the next page

Table 3.2: Major crisis events

Modelling crisis			
Year	Transmission- Markets	Vulnerability-markets	Crisis events
2012:1	Germany, UK, France, Chili, Greece, Austria, Canada	Singapore, South Korea,USA, Japan, Nigeria, Venezuela	Eurozone crisis continues
2012:2	Germany, UK, France, New Zealand, Nigeria	India, Singapore, South Korea, Chili	
2013:1	Greece, Portugal, Ireland, Venezuela	India, Austria, Canada, Norway, New Zealand	Eurozone crisis continues
2013:2	India, Chili, Austria, Russia, Norway	Germany, France, Croatia, Japan	Eurozone crisis continues
2014:1	India, Chili, Austria, Russia, Norway	Germany, France, Croatia, Japan	Commodity price drops with the slowdown in Chinese economy, also contributing into a large scale Brazilian economic crisis.
2014:2	Russia		**2014-2015 Russian Financial crisis**: Following economic sanctions on Russia, plummeting global oil prices, devaluation of Russian ruble and fire sale of Russian assets all contributed in the development of a major financial crisis in Russia.
2015:1	Greece, Croatia, Austria, Saudi Arabia, Nigeria, Venezuela	Chili, Belgium, Austria, Canada, Norway, New Zealand, Israel, Nigeria, Venezuela	
2015:2	China, Canada	India, The Philippines, South Korea,USA, Russia, Japan	Corresponding to Russian Financial crisis, stock market in the USA starts to decline.
2016:1	China, Venezuela	India, The Philippines, Singapore, South Korea, France, Australia, Greece, Portugal, Belgium, Austria,USA, Russia, Norway, Japan, Saudi Arabia, Sri Lanka, Nigeria	**1**. **Export Crisis**: Germany, Chile, France, China, UK, Australia among others experience historic decline in total exports to others, followed by the so-called oil-glut. **2**. **Chinese crisis**: A massive drop in Chinese stock markets results in markets terminating transactions in the wake of concerns over a Chinese Crisis, that eventually took the shape of a global meltdown. **3**. January 2016 global meltdown resulting from fire sales of Chinese assets brought down the European and the USA stock markets
2016:2		Greece, Portugal, Croatia, Austria, Russia, Japan	

continue on the next page

Table 3.2: Major crisis events

	Modelling crisis		
Year	Transmission- Markets	Vulnerability-markets	Crisis events
2017:1	UK, Australia, France, Chili, Greece, Portugal, Ireland, Belgium, Croatia, Austria, Japan, New Zealand, Israel, Nigeria, Venezuela	China, Russia, Japan, New Zealand	2016 global meltdown continues
2017:2		China, Australia, Chili, Ireland,USA, Canada, Russia, Japan, New Zealand, Saudi Arabia, Nigeria, Venezuela	

Table 3.3: Generalized variance decomposition Matrix measured with DY method, on all vectors across full sample. A full description is presented in 'Empirical framework' section in the paper.

														From																
To	USA	AUS	IND	JAP	MYS	NZL	SGP	PHL	KOR	SLK	THA	NGA	VEN	KWT	IRQ	SAU	CHN	ISR	CAD	GRC	PRT	IRL	BEL	HRV	AUT	RUS	NOR	GER	CHL	UK	FRA	Total
USA	16.74	1.491	2.877	0.548	0.551	1.791	4.386	0.725	3.569	0.025	2.846	0.041	0.018	0.057	0.073	0.666	0.117	7.281	28.98	3.962	6.170	7.647	13.76	3.219	10.91	6.956	15.59	30.34	17.67	18.54	24.22	231.8
AUS	3.471	13.44	6.869	6.479	4.034	14.78	11.43	3.559	9.143	0.115	8.428	0.127	0.034	0.107	0.115	1.014	1.992	4.549	19.70	5.852	7.980	7.503	12.09	8.008	18.10	8.309	24.07	16.52	19.23	16.04	17.81	270.9
IND	1.055	0.075	58.46	0.562	1.015	0.404	2.883	0.964	2.519	0.199	2.971	0.197	0.013	0.101	0.059	0.331	0.446	2.439	3.668	1.329	1.635	1.521	2.561	1.025	2.433	3.186	2.195	4.449	7.207	2.221	4.240	112.3
JAP	2.006	0.108	0.466	49.06	0.648	0.132	2.564	0.471	3.341	0.079	1.779	0.077	0.004	0.068	0.104	0.445	0.175	0.543	3.942	0.618	0.457	0.401	1.278	0.522	1.136	1.293	0.968	3.421	3.862	1.882	3.879	85.74
MYS	0.932	0.044	0.048	0.295	65.35	0.037	3.389	1.517	1.272	0.038	4.502	0.016	0.033	0.013	0.026	0.071	0.092	0.676	2.679	0.156	0.652	0.239	1.310	1.536	0.703	2.415	1.006	0.916	4.108	0.628	2.011	96.72
NZL	2.162	0.075	0.613	0.023	0.081	27.37	1.339	0.447	0.450	0.261	1.087	0.087	0.002	0.050	0.018	0.189	0.027	1.224	6.044	1.396	2.173	1.941	3.861	2.163	3.699	1.588	3.842	5.727	5.562	3.509	4.928	81.94
SGP	1.490	0.065	0.142	0.732	0.217	0.117	37.24	2.308	2.296	0.431	9.439	0.015	0.095	0.064	0.012	0.037	0.175	1.533	4.853	0.996	0.692	0.709	2.638	0.603	1.529	2.855	2.318	2.983	5.619	2.412	3.594	88.22
PHL	1.845	0.101	0.496	0.473	0.173	0.164	1.159	53.47	1.222	0.104	5.557	0.079	0.007	0.154	0.021	0.129	0.098	1.702	4.686	0.581	0.955	1.034	3.650	0.704	1.718	1.959	2.001	3.632	8.744	2.162	3.676	102.4
KOR	2.425	0.464	0.740	1.429	0.162	0.270	1.742	0.502	56.44	0.088	2.489	0.175	0.016	0.133	0.025	0.361	0.503	1.887	6.693	1.032	1.566	1.245	4.656	0.972	1.480	3.082	2.096	8.230	7.657	3.914	7.142	119.6
SLK	0.104	0.008	0.093	0.134	0.047	0.121	0.035	0.009	0.063	88.22	0.072	0.118	0.006	0.115	0.030	0.223	0.063	0.125	0.237	0.045	0.223	0.175	0.599	0.591	0.227	0.152	0.644	0.401	0.825	0.453	0.107	94.26
THA	1.096	0.108	0.084	0.409	0.254	0.276	0.548	0.784	1.002	0.037	68.24	0.043	0.009	0.063	0.007	0.122	0.392	0.546	4.325	0.455	0.69	0.596	2.003	0.954	0.481	2.026	1.035	1.978	8.504	0.885	2.929	100.8
NGA	0.069	0.063	0.012	0.048	0.031	0.053	0.019	0.044	0.006	0.041	0.032	96.00	0.023	0.037	0.045	0.502	0.055	0.034	0.168	0.059	0.100	0.097	0.182	0.137	0.024	0.225	0.123	0.154	0.149	0.068	0.094	98.70
VEN	0.185	0.248	0.097	0.413	0.019	0.274	0.184	0.137	0.637	0.092	0.108	0.028	97.34	0.012	0.015	0.379	0.889	0.632	1.336	0.978	4.262	0.256	0.395	0.184	0.618	0.706	0.539	0.579	3.156	2.395	0.556	117.6
KWT	0.101	0.229	0.286	0.196	0.101	0.108	0.353	0.252	0.009	0.709	0.114	0.206	0.003	95.64	0.003	0.789	0.122	0.664	0.072	0.249	0.382	0.474	0.176	0.269	0.418	0.982	0.138	0.356	0.126	0.288	0.646	104.4
IRQ	0.208	0.094	0.079	0.208	0.125	0.173	0.136	0.145	0.408	0.458	0.470	0.419	0.005	0.190	96.95	1.178	0.095	0.806	0.103	0.501	0.346	0.181	0.495	0.621	0.651	0.515	0.367	0.656	2.235	0.148	0.443	109.4
SAU	0.223	0.017	0.169	0.134	0.032	0.024	0.296	0.152	0.338	0.154	0.040	0.028	0.001	0.024	0.015	82.68	0.257	0.414	1.303	0.389	0.403	0.336	0.665	0.396	0.658	0.800	1.696	0.873	0.995	0.517	0.540	94.57
CHN	0.101	0.050	0.049	0.196	0.018	0.003	0.089	0.208	0.045	0.103	0.019	0.012	0.001	0.005	0.017	0.105	94.24	0.134	0.401	0.205	0.065	0.223	0.772	0.192	0.263	0.122	0.152	0.791	1.305	0.109	0.207	100.2
ISR	1.335	0.189	0.698	0.089	0.047	0.039	0.440	0.274	0.262	0.067	0.137	0.010	0.005	0.019	0.011	0.329	0.124	46.60	5.150	1.854	2.242	1.952	3.264	2.019	4.128	2.812	5.862	6.935	3.995	3.464	6.674	101.0
CAD	1.153	0.311	0.511	0.160	0.133	0.123	0.899	0.124	0.417	0.072	0.230	0.056	0.012	0.013	0.001	0.089	0.013	0.704	34.17	1.322	2.304	0.975	3.481	2.244	3.840	3.202	8.616	6.499	6.483	4.375	5.363	87.91
GRC	2.857	0.034	0.629	0.022	0.082	0.286	1.019	0.131	0.239	0.093	0.085	0.042	0.007	0.017	0.034	0.119	0.187	1.409	6.257	53.38	8.376	5.483	12.45	4.563	10.10	2.789	7.043	16.75	7.628	5.774	12.22	160.1
PRT	1.588	0.089	0.539	0.011	0.012	0.067	0.328	0.082	0.386	0.029	0.106	0.029	0.002	0.015	0.003	0.021	0.068	0.666	2.930	1.156	33.47	5.540	12.78	3.982	12.50	1.716	6.809	16.94	6.702	6.194	17.21	131.9
IRL	3.342	0.277	0.655	0.250	0.015	0.228	1.408	0.278	0.814	0.003	0.494	0.056	0.008	0.017	0.016	0.494	0.109	1.442	6.312	1.558	1.744	32.75	11.13	2.581	8.032	2.568	5.512	12.45	6.578	9.331	9.241	119.7
BEL	2.144	0.179	0.675	0.023	0.044	0.118	0.695	0.173	0.458	0.012	0.101	0.033	0.001	0.003	0.003	0.203	0.089	0.936	4.252	0.900	0.970	0.857	32.91	1.893	5.363	1.249	4.582	14.89	4.558	5.828	10.74	94.90
HRV	1.898	0.041	0.494	0.358	0.080	0.071	0.809	0.137	0.224	0.267	0.181	0.006	0.006	0.040	0.018	0.394	0.009	0.971	2.464	0.538	0.970	1.034	2.341	67.09	2.855	1.707	2.059	3.449	4.841	0.975	2.175	98.52
AUT	1.965	0.193	1.035	0.007	0.012	0.217	1.105	0.129	0.579	0.047	0.253	0.041	0.008	0.016	0.009	0.305	0.027	0.657	4.749	1.199	1.329	1.349	4.034	0.836	31.77	2.930	6.844	5.322	6.124	2.635	3.617	79.35
RUS	2.391	0.088	0.860	0.258	0.219	0.585	1.288	0.519	0.255	0.544	0.071	0.193	0.008	0.038	0.015	0.090	0.243	0.400	9.777	0.674	1.137	0.300	2.014	2.184	2.418	75.29	5.104	6.429	11.71	4.427	2.286	131.8
NOR	3.252	0.316	1.001	0.224	0.009	0.208	1.071	0.308	0.649	0.082	0.384	0.074	0.006	0.014	0.014	0.327	0.087	0.987	10.16	1.652	1.832	1.241	4.853	1.461	2.352	2.185	40.47	7.899	6.159	4.569	5.528	99.37
GER	3.090	0.322	0.996	0.173	0.073	0.227	1.011	0.107	0.748	0.019	0.313	0.040	0.005	0.012	0.003	0.242	0.048	1.937	6.104	1.409	1.817	1.525	5.608	1.182	3.202	2.395	2.849	37.32	5.308	5.100	13.38	96.57
CHL	0.693	0.105	0.166	0.051	0.040	0.061	0.205	0.046	0.066	0.091	0.119	0.083	0.001	0.014	0.004	0.077	0.006	0.376	1.247	0.218	0.389	0.287	1.239	0.337	0.373	0.489	0.850	1.522	69.95	0.732	1.133	80.97
UK	3.444	0.488	1.074	0.202	0.054	0.398	1.297	0.228	0.889	0.013	0.504	0.050	0.008	0.043	0.003	0.248	0.061	1.503	7.437	1.637	1.929	1.848	5.853	1.247	3.801	2.167	3.777	8.037	5.227	22.53	6.341	82.34
FRA	3.403	0.416	1.043	0.192	0.087	0.438	1.193	0.162	0.937	0.007	0.324	0.037	0.008	0.023	0.003	0.322	0.052	1.849	6.836	1.742	2.201	1.521	5.439	1.205	3.344	2.252	3.273	8.669	5.072	2.905	17.78	72.73
Total	66.78	19.73	81.97	63.36	73.77	49.17	80.57	68.41	89.69	92.51	111.5	98.43	97.70	97.13	97.67	92.48	100.8	85.63	197.1	88.05	89.46	81.24	158.5	114.9	139.1	140.9	162.4	235.1	247.3	135.0	190.7	

Table 3.4: Summary statistics of 10 basis crisis classification

Actual	1998:1	1998:2	1999:1	1999:2	2000:1	2000:2	2001:1	2001:2	2002:1	2002:2	2003:1	2003:2	2004:1	2004:2	2005:1
Min.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1st Qu.	1.00	6.00	5.00	6.00	1.00	5.00	5.00	6.00	6.00	1.00	4.00	5.00	1.00	1.00	4.00
Median	3.00	7.00	7.00	6.00	4.00	6.00	6.00	7.00	7.00	5.00	5.00	5.00	4.00	5.00	6.00
Mean	3.92	5.95	**6.22**	6.19	3.55	5.50	5.24	**6.40**	**6.65**	4.50	4.64	5.12	3.78	4.75	5.19
3rd Qu.	7.00	7.00	7.00	7.00	6.00	7.00	7.00	7.00	7.00	7.00	7.00	6.00	6.00	7.00	7.00
Max.	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Actual	2005:2	2006:1	2006:2	2007:1	2007:2	2008:1	2008:2	2009:1	2009:2	2010:1	2010:2	2011:1			
Min.	1.00	1.00	1.00	1.00	3.00	1.00	3.00	3.00	1.00	1.00	1.00	1.00			
1st Qu.	1.00	8.00	5.00	8.00	8.00	4.00	8.00	3.00	3.00	3.00	3.00	4.00			
Median	6.00	8.00	5.00	8.00	8.00	6.00	8.00	9.00	3.00	3.00	6.00	9.00			
Mean	4.65	**7.58**	5.78	**7.90**	**8.15**	6.17	**8.08**	**6.98**	5.20	5.39	**6.84**	**6.96**			
3rd Qu.	7.00	8.00	8.00	9.00	10.00	9.00	10.00	10.00	8.00	9.00	10.00	9.00			
Max.	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00			
Prediction	2011:2	2012:1	2012:2	2013:1	2013:2	2014:1	2014:2	2015:1	2015:2	2016:1	2016:2	2017:1			
Min.	3.00	3.00	3.00	4.00	1.00	1.00	1.00	1.00	4.00	1.00	1.00	1.00			
1st Qu.	3.00	6.00	4.00	5.00	4.00	4.00	4.00	4.00	6.00	8.00	4.00	4.00			
Median	3.00	9.00	6.00	5.00	4.00	4.00	6.00	5.00	9.00	8.00	5.00	5.00			
Mean	5.17	**8.35**	5.92	5.59	4.94	4.86	5.37	5.45	**8.01**	**7.94**	5.30	4.95			
3rd Qu.	8.00	10.00	6.00	6.00	6.00	6.00	6.00	6.00	10.00	9.00	9.00	7.00			
Max.	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00			

Table 3.5: Summary statistics of 900 basis crisis classification

Actual	1998:1	1998:2	1999:1	1999:2	2000:1	2000:2	2001:1	2001:2	2002:1	2002:2	2003:1	2003:2	2004:1	2004:2	2005:1
Min.	51.00	3.000	19.00	8.000	2.000	11.00	37.00	39.00	59.00	21.00	48.00	25.00	129.00	45.00	80.00
1st Qu.	421.0	181.0	253.0	127.0	309.0	92.00	322.0	256.0	317.0	243.0	280.0	266.0	287.0	247.0	382.0
Median	536.0	430.0	535.0	348.0	561.0	460.0	456.0	533.0	544.0	377.0	543.0	610.0	524.0	601.0	548.0
Mean	**550.0**	436.0	**515.2**	353.5	500.9	360.3	502.9	509.1	**523.2**	428.0	464.9	506.6	**530.8**	524.8	497.7
3rd Qu.	780.0	699.0	790.0	455.0	696.0	532.0	846.0	751.0	729.0	675.0	679.0	802.0	713.0	844.0	616.0
Max.	959.0	871.0	950.0	945.0	937.0	869.0	953.0	961.0	896.0	931.0	955.0	944.0	955.0	934.0	868.0
Actual	2005:2	2006:1	2006:2	2007:1	2007:2	2008:1	2008:2	2009:1	2009:2	2010:1	2010:2	2011:1			
Min.	28.00	36.00	12.00	6.000	24.00	1.000	13.00	43.00	83.00	64.00	1.000	7.000			
1st Qu.	198.0	222.0	175.0	305.0	345.0	228.0	85.00	462.0	185.0	385.0	142.0	126.0			
Median	453.0	371.0	390.0	517.0	504.0	415.0	252.0	633.0	412.0	660.0	254.0	308.0			
Mean	463.4	**470.6**	392.3	**513.8**	**563.2**	464.7	345.2	**607.2**	**498.2**	**545.9**	413.6	431.3			
3rd Qu.	775.0	762.0	588.0	683.0	821.0	795.0	553.0	849.0	902.0	707.0	678.0	712.0			
Max.	920.0	949.0	946.0	957.0	941.0	914.0	900.0	952.0	951.0	927.0	948.0	958.0			
Prediction	2011:2	2012:1	2012:2	2013:1	2013:2	2014:1	2014:2	2015:1	2015:2	2016:1	2016:2	2017:1			
Min.	30.00	64.00	30.00	1.000	4.000	102.0	17.00	1.000	33.00	70.00	16.00	5.000			
1st Qu.	298.0	214.0	234.0	279.0	167.0	475.0	211.0	337.0	106.0	268.0	290.0	205.0			
Median	404.0	466.0	442.0	478.0	411.0	566.0	440.0	489.0	301.0	506.0	406.0	389.0			
Mean	475.7	**485.3**	480.1	**494.4**	439.6	**573.4**	457.9	**524.4**	362.4	507.4	491.1	445.2			
3rd Qu.	736.0	698.0	673.0	720.0	786.0	758.0	741.0	726.0	604.0	725.0	788.0	741.0			
Max.	956.0	960.0	912.0	925.0	921.0	937.0	954.0	957.0	951.0	908.0	951.0	910.0			

Chapter 4

Contagion or interdependence? Comparing signed and DY spillovers

4.1 Introduction

We investigate spillover patterns in the markets by assessing global equity market interdependence with the Diebold and Yilmaz (DY) connectedness index (Yilmaz et al., 2018; Demirer et al., 2018a,b; Yilmaz, 2017; Diebold et al., 2017b; Diebold and Yilmaz, 2015; Diebold and Yılmaz, 2014) against the multivariate historic decomposition (MHD) index(Dungey et al., 2017b). Both complement the measurements of the information in a VAR. The DY provides information on the direction and size of spillovers, while the MHD provides the direction, size and sign, that is, whether the linkages dampen or amplify shock transmission. We calibrate the MHD further by the estimating signed index with realised variances, and separate out the self exciting transitory signed volatility evolution from the signed return spillovers with our proposed SVD. This approach can be considered as an extension of vulnerability and transmission representations with MHD. **Besides presenting comparisons** with three different identification approaches and extracting more information on risks generated within the intertwined markets, the main finding of this chapter is that juxtaposed identification approaches allow us to focus out systemic risk edges that are overlain with time varying volatility using a single approach. By doing so, this chapter addresses a key argument with treating contagion and volatility separately.

In this chapter, we address five key arguments concerning the time-varying nature of systemic risk estimates leading to the detection of crisis transmission patterns. First, we examine whether policy interventions that restrict significant transmission paths help interconnected financial markets weather shocks. Second, we find that the changing interactions between markets result in changing patterns of shock spillovers. Third, we examine whether it is possible to detect which markets are more shock resistant in the sample period from 1998–2017. Fourth, we determine if a parametric signed identification approach can be used as an extension to the DY identification approach of return spillovers. Fifth, we examine if signed indices computed with non-parametric gauges [1] points out self-exciting volatility transmissions from return transmissions.

An important concern arising from the listed questions may be, why these questions are important or how they connect to a key logical argument that enhances our state of

[1]This yields realised volatility transmissions within a predefined system.

knowledge. A key contribution of this chapter that it enhances our state of knowledge by realising the importance of a signed index in explaining crises only and not contagion.

A novelty in our nested technique is that crisis demarcation is not a necessary condition for contagion identification. We do not need to concur with Forbes and Rigobon (2002) in knowing the crisis and calm periods to separate contagion from interdependence. We support the work of Dungey and Renault (2018) while **progressing the current tenet by identifying** the more contagious markets from the less contagious or not contagious markets with a single approach. **This is a key contribution to the current literature** investigating the real time evolution of contagion and, by extension, the early warning literature.

We apply DY, MHD and SVD approaches to a large panel of international equity markets. The DY provides a profile of increasing spillover effects between the markets across the sample period, highlighting periods of change in the intensity for these effects. **However, the DY is limited in identifying** the direction of contemporaneous risk measures. MHD analysis enhances the DY by identifying linkages between markets that amplify or dampen shocks and, further, how the system of markets fluctuates around the average relationship by accumulating shocks over time. MHD helps discerning negative in-shocks from positive out-shocks with signs. SVD analysis complements MHD by calibrating the model with innovations from realised variance estimates put into a generalised impulse response function. We show that the results are robust to choices over rolling samples and alternative data frequency choices.

Our results also allow us to focus on the potential risks of crisis, and the emergence of China as an important conduit market as outlined in a number of studies (Elliott, 2017; Mullen, 2017; Quijones, 2017; Mauldin, 2017; Friedman, 2016; Jolly and Bradsher, 2015).

We identify the most crisis-prone markets and explain how the effect of innovations in these markets are different from the less crisis-prone markets. The inclusion of an oil index allows us to examine the system's sensitivity to shocks, especially during periods of stress in oil supplies. The stress coming from exogenous shocks are examined only with the DY spillover measure.

We follow an ordered structure in introducing novelty in this paper. First, we implement the DY measuring spillovers between financial entities. We find increased resilience in the financial networks corresponding to policy interventions in response to a crisis, and also evidence of previously resilient markets becoming susceptible to new shocks. This is particularly clear since the advent of the European debt crisis. We also find strong evidence of changing interconnectedness between markets, particularly associated with increased interaction between markets over time. We do this using a rolling connectedness index. However, this has been done many times in past studies with the DY, and only provides a basis from which to introduce our approach. Second, we compare the outcomes with the signed historic decomposition index proposed by Dungey et al. (2018b) which separately identifies shocks amplifying and dampening between markets, overcoming the limitations of absolute value representation of the DY. Finally, we propose an SVD index with realised variance estimates comparing if SVD yields volatility transmission patterns differently from MHD and the DY. **We also examine if SVD complements MHD and adds to the robustness of MHD.**

It is important to understand the implications of systemic risk changing the degree of crisis propagation in the markets listed in our system, leading to holistic measures gauged from the methods discussed here. Thus, it is crucial to discuss the dynamics in the contemporaneous associations between markets in the past. In the next section, we discuss briefly the history of crises spanning across the sample markets.

4.1.1 A brief history of crises changing connectivity for the sample markets

Asian crisis

With the unveiling of the 1997–1998 Asian financial crisis, supervisors attempted to stem the falling markets by responding differently from each other. As the ground zero of the crisis, Thailand adopted a structural adjustment package. The crisis disproportionately affected other countries, driving the supervisors of Malaysia, Indonesia and South Korea to adopt policies pulling in different directions. While Malaysia reverted to a fixed exchange regime, Indonesia's inflation targeting policy and South Korea's currency devaluation floated the exchange rates in both the countries (Khan and Park, 2009). Among others, Singapore continued with its managed currency float, while Chinese authorities avoided any degree of intervention into the markets (Raghavan and Dungey, 2015). While the Asian markets successfully stopped the crisis from propagating further, the resulting changes in the interconnections within and outside the markets provided a clearer picture of the strengths and weaknesses of the AC cluster.

War and oil shock

The extant literature posits a perennial question associating war with crisis. Major relevant studies have attributed this to holding either a 'liberalist' view or 'realist' view, taking opposite stands while describing the economic costs of war (Morrow, 1997; Barbieri, 2002; Li and Sacko, 2002; Schneider and Troeger, 2006b). As war erupts, provided there is heightening of military goods trade relative to little or no drop in bilateral trade, Morrow (1997); Barbieri and Levy (1999); Barbieri (2002) supported the 'relative gain' concept. Albeit belonging to the liberalist view, Schneider and Troeger (2006a) supported the realist view provided short-term spikes in financial markets reflected increased investor confidence. This is partly due to investors' belief that positive anticipation of war outcome is conducive to escalating trade and asset returns. This anticipation also held for higher oil returns during the Iraq invasion. However, there exists little empirical evidence in the extant literature in support or in opposition to this view, resulting mostly in exacerbation or downplay of the true economic casualty that may emerge from war.

Li and Sacko (2002) and Schneider and Troeger (2006a) also presented two financial market scenarios with fundamental models prevailing in finance. If a long term uncertainty is associated with a conflict, investors collectively sell off stocks and seek investment into less risky assets elsewhere, sending local markets into a cascade. In contrast, positive expectations stemming from news related to the quick resolution of war may increase investment as higher returns are attributed to the winning of war. In any case, all different views in outbreak of the wars affecting financial markets converge into an accord that war has a negative effect on economic exchange (Barbieri and Levy, 1999; Barbieri, 2002).

Rigobon and Sack (2005) reported a subsequent decline in the equity prices, treasury yields and dollar rates as the USA invaded Iraq. Leigh et al. (2003) provided an extension to gauge the direction of equity investments from a 'Saddam Security' futures, suggesting a global decline in asset values once the full extent of effect of Iraq is realised. This also lends support to heightened capital flights as explained by Schneider and Troeger (2006a), causing increased connectedness and systemic risk. Schneider and Troeger (2006a) further suggested that investors generally fail to adapt to prolonged political uncertainty, and this is reiterated by transmitting crisis globally, especially through stock markets.

Leigh et al. (2003) provided a rationalisation for cascading international equity markets resulting from systemic transmission of crisis immediately after the Iraq invasion. For each 10 per cent increase in the probability of war the drop in the the stock prices of Germany, Sweden, Taiwan, Israel, Venezuela and, Hong Kong accounts for over 3 per cent. The price drops for the USA, Portugal, Netherlands, Singapore, China, France, the Philippines, the UK, Russia, Norway, Canada remains within 2 to 3 per cent. Australia, Belgium, Chile, Thailand, India, Japan, Greece, Malaysia, Sri Lanka, Austria and, Indonesia are burdened with 1 to 2 per cent drops in asset prices. Indeed, as the war deepens longer than expected, the drops continue to escalate for each additional degree of probability, sending many markets into a downward spiral.

Leach (2003) addressed the conditions in Japan and the European Union zone particularly concerning the worsening economic spirals transmitted by the USA recession. In the past, the buoyant Japanese and the European Union stock markets successfully offset crisis build-up when the USA was at war with Vietnam, and vice versa. However, in the impending Iraq invasion period, both economies were submerged in domestic crises that were compounded by the burdening Iraq War. The systemic failure in the Japanese economy was well advanced, with bank loan defaults adding upto 35 per cent of its GDP, leading to cascades of bank failures. This situation escalated with constraints imposed on further stimulus facing a phenomenal public debt level. The Eurozone faced imposing fiscal constraints outlined in the 'Growth and stability pack' coupled with accelerated inflation as Germany slipped into recession.

In contemplating the global economic contraction facing a war-like crisis between two players, a key state variable is oil price fluctuation. Leach (2003) held that because the cost of oil is implicit in the cost of business, the conflicting inflationary pressure on the oil market that conflicts leads to contractionary monetary policies that hike interest rates. This, in turn, spurs unemployment and sets the economy off on a cascade. The downturn is severe, particularly for oil exporting countries, and results from exchange rate jumps that is termed as the 'petrocurrency effect'. Nordhaus (2002) presented a predictive analysis for the USA market; in the advent of an Iraq-invasion, that an oil shock may bring about a US$17 billion gain compared to a US$800 billion loss in the years that follow the invasion. In this study, we attempt to disentangle the oil effect in gauging systemic risks by including oil as an entity in the system.

The number of commentator concerns over the issue of war causing oil price fluctuation subsided as the GFC ensued. Early 2006 marked a period of general buoyancy in the markets across all sectors. Lending contractions in the financial sector that followed were due in large part to the unprecedented level of subprime mortgages, which led to the entire USA economy becoming susceptible to an imminent meltdown. Dungey et al. (2018c) illustrated that, despite the economy facing an overall subprime crisis, the abrupt offloading of risky exposures through credit risk transfers only exacerbated the economic downturn. In the full form of the USA subprime crisis in September 2008, several leading investment institutions started to feel the pinch with a series of events, which led to the Lehmann Brother bankruptcy, sheer fall of mortgage-backed securities reflected in the ABX index, government bailing the AIG out and taking Fannie Mae and Freddie Mac over. While in the US, supervisors tried to control the swings of crisis with bailout packages and a TARP contract, the high degree of international investments into the cascading USA mortgage backed securities sent markets across borders into a downward spiral.

Eurozone crisis

Shortly after came the fiscal crisis in Greece in 2009, which mutated into a deep recession through a sovereign debt crisis in the years that followed. The announcement of Greece's budget deficit had increased to five times higher than the target stipulated by Growth and Stability Pact spurred fear over the future of eurozone. Matsaganis (2013) held that with the adoption of new austerity measures by the local government in the following years, coupled with depletion of Greece's credit rating, investors naturally cause further degradation of returns on investment in Greek market. This resulted in cascading capital in the Greek market that pushed the economy into a solvency crisis. The conditions to adopt more austerity measures that came with bailout packages by the International Monetary Fund and the European Union only exacerbated the worsening spiral for Greece. Consequently, by the end of 2013, the Greek standard of living had dropped to 34.3 per cent below average (Matsaganis, 2013). This crisis had spread quickly, with Spain and Portugal each losing about 8 per cent living standards. The economic contraction, as indicated in the Eurostat statistics database, stood at 23.5 per cent for Greece, and had simultaneously contracted the economies of Spain by 5.5 per cent, Portugal by 7.4 per cent, Italy by 7.8 per cent and Ireland by 5 per cent (Matsaganis, 2013).

The escalating European debt crisis provided an ideal foundation from which to investigate the channels of GFC that expedited European debt crisis's build-up. The work of Reinhart and Rogoff (2011) is considered the first to have proposed causal connections between the banking and debt crisis. While endorsing this concept, Candelon and Palm (2010); Angeloni and Wolff (2012) and De Bruyckere et al. (2013b) empirically established the notion that the subprime crisis mutated into sovereign debt crisis, rationalising the systematic build-up of the European crisis stemming from the GFC. Recently, Calabrese et al. (2017) indicated that systemic risk due to simultaneous debt holdings between Greece, Italy, Ireland, Portugal and, Spain (GIIPS) was responsible for spurring the European debt crisis. Ruščáková and Semančíková (2016) classified the crisis channels into banking and fiscal.

Risks generated from the financial sector disproportionately affect the real economy, especially when the effects of financial sector stocks are separated from non-financial stocks, as Dungey and Renault (2018) suggested. By disentangling risk transmission from different sectors in the USA stock markets, Dungey et al. (2018c) provided evidence that non-financial sector equities shield the real economy as a crisis intensifies. Having access to alternative sources of credit, non-financial sector portfolios decouple with the heightening of systemic risk, and provide a partial hedge to domestic investors. This finding explains how some smaller economies with a disproportionate allocation of financial sector and non-financial sector undertakings offset the effects of crisis despite domestic banks bearing the full brunt of a crisis emitting from global banks and not the other way around.

More recently, Dungey et al. (2018a) provided the rational that all euro-zone markets do not have the same reassessment for potential default risk. Dungey et al. (2018a) found evidence for prolonged crisis regimes with 'durations' of high-volatility for GIIPS, including Belgium, Spain and Netherlands. Conversely, crisis regimes for Germany and, the UK were more short-lived. Moreover, Dungey and Renault (2018) asserted that Germany provides a safe haven during crisis, as markets susceptible to volatility resulting from contagion distance themselves somewhat from Germany.

The emergence of Brazil, Russia, India and China (BRIC)

The relative importance of systemic risks pertaining to interdependence, or risks emerging from sufficiently proximate contemporaneous small shocks for Brazil, Russia, India and China (BRIC) is, a priori, attributable to their recent transformation into leading investment avenues. The impetus given by the utmost global depository receipt issuance, coupled with hasty equity market liberalisation, positioned the Chinese (Shanghai Stock Exchange) and Indian (Bombay Stock Exchange) markets as the fourth- and fifth-largest trading platforms in the world. However, these markets did not suffer from the same market reassessment of default risk when faced with the 2007 meltdown, as India and Russia observed a sharp increase in negative inflows while for China, these inflows remained positive (Chittedi, 2014). This led to a cascade, as liquidity that drained from the emerging markets brought about local currencies falling sharply against dollars (Ferreiro and Serrano, 2011).

There is a substantial literature that both supports and contradicts such views. Immediately following the GFC, Dooley and Hutchison (2009) and Dimitriou et al. (2013) dismissed contagion transmissions into BRIC, including East Asia emanating from the US. More recently, Wang (2014) and Syriopoulos et al. (2015) complemented this notion by finding increased interconnections between the USA and East Asian markets alongside their BRIC counterparts; however, this was observed only after the GFC. In contrast, Bekiros (2014) found that contagion spurred the relevant markets with the unfolding of GFC.

Equity shortfall in Europe during GFC

Similar to BRIC and the Asian markets, capital flights from equity markets of Eastern Europe in the advent of the GFC pushed the market values of stocks down by 50 per cent. Syllignakis and Kouretas (2011) asserted that institutional investors shifting investment preferences from stocks and bonds to treasury bills, with the preceding investment withdrawal from institutional to investor-managed, emerging market hedge funds and private equity by investors as the USA subprime crisis unfolded exacerbated crisis transmission and contagion in the emerging Eastern European markets. Evidently, connectivity between emerging and European export dominant countries had resurfaced, especially with Germany, Russia, the UK and the USA (Syriopoulos, 2007; Lucey and Voronkova, 2008; Syllignakis and Kouretas, 2010).

In what follows we present the empirical framework concerning GVD, static and dynamic networks, MHD and SVD in section 4.2 followed by Section 4.3 that outlines the dataset, consisting of 30 equity markets, the oil index and the commodity index. This section also presents the filtering method and descriptive statistics on filtered data. Section 4.4 discusses the empirical results based on 'system-wide connectedness' and the resultant network among the markets, before following on to the dynamic analysis and MHD measures explaining the effect of positive and negative shocks in the sample markets. We compare the results of MHD with SVD in this section. Section 4.5 presents the conclusion to this chapter.

4.2 Empirical framework

The complete n-step ahead forecast error variance decomposition matrix in a VAR framework proposed by Diebold and Yilmaz (2012) is presented in Chapter 2. This framework generates vulnerability indices gauged from DY spillover indices.

4.2.1 Multivariate historical decomposition (MHD)

The historic decomposition pioneered by Dungey et al. (2017a), produces a signed contribution of shocks from one to another that captures the magnifying and dampening effects of contemporaneous shocks in the intertwined markets. Here, the connectedness elements measured with A_{ij} explain the fraction of variation of i due to shocks in j at time t (excluding self-loops in a network). The structural parameters are estimated with OLS from the equation as follows

$$x_t = \sum_{i=1}^{k} \phi_i x_{t-i} + \varepsilon_t \tag{4.1}$$

Here, $x_t = [x_{1,t} \dots x_n, t]^T$. Next, re-writing the reduced form VAR with disturbances and representing with moving averages we have

$$x_t = \textit{initial values} + \sum_{i=0}^{\infty} S_i \varepsilon_{t-i} \tag{4.2}$$

Here, $S_j = \varphi_1 \varphi_{j-1} + \varphi_2 s_{j-2} + \dots$ with $j = 1, 2, \dots, S_0 = I_N$ and $S_j = 0$ for $j < 0$. Re-writing this equation for any individual element $x_{j,t}$, which can be explained with contributions of all other elements, the third step, represents the historical decomposition of j at time t. This is presented in the equation as follows,

$$HD_{t+j} = \sum_{i=0}^{j-1} IRF_i \odot \gamma_{t+j-i} + \sum_{i=j}^{\infty} IRF_i \odot \gamma_{t+j-i} \tag{4.3}$$

Here, $\gamma_{t+j-i} = [\varepsilon_{t+j-i}, \dots \varepsilon_{t+j-i}]$ is an $N \times N$ sized residual matrix, with N representing the length of a vector. IRF_is' are one unit impulse responses (non-orthogonalised) and $\odot$ is the Hadamard product . The estimated MHD produces an $N \times N$ sized matrix providing negative in-shocks across the rows and positive out-shocks down the columns of the matrix without any sign restriction. This approach accommodates the non-linear dynamics of the data .

Here, MHD produces signed weights of shocks throughout the channels, as a function of impulse responses weighted by residuals ε_t. The system uses unconditional variance estimates as innovations for the impulse response estimates and, as such, are considered to represent spillovers in the returns of the variances.

Next, we propose a signed volatility spillover decomposition matrix by calibrating the MHD model with conditional variances estimated in a GARCH framework. This will allow us to compare the volatility spillover of the indices to the return spillovers presented in MHD.

4.2.2 Signed volatility decomposition

In this section we propose SVD extracting spillover information drawn from realised variances associated with volatility transmissions within networks, **which also serve as a robustness for MHD.** We take the difference between return and volatility spillovers to identify whether a particular market is driven more by intrinsic volatility than by risks emerging from the network.

We take a non-parametric approach to estimate SVD, which follows the same algorithm as MHD. Unlike MHD computed from daily returns, we compute MHD from realised variance drawing from five-minute intervals in prices and, as such, the historic decomposition is depicted as SVD.

We begin by calculating log returns with $r_t = log(P_t) - log(P_{t-1})$. Next, we take squared returns of five- minute intraday data and sum them up to find daily realised variances with

$$RV_t = \sum_{i=1}^{N} r_t^2 \tag{4.4}$$

All else remaining constant, SVD is the historic decomposition presented earlier

$$SVD_{t+j} = \sum_{i=0}^{j-1} IRF_i \odot \gamma_{t+j-i} + \sum_{i=j}^{\infty} IRF_i \odot \gamma_{t+j-i} \tag{4.5}$$

To identify contagion in the holistic associated network from volatility of common factors localised to a given market we simply take the spread between SVD and MHD.

$$Spread_{t+j} = SVD_{t+j} - MHD_{t+j} \tag{4.6}$$

4.3 Data

The data are daily dollar denominated stock returns from 30 developed and developing countries' markets across Asia–Pacific, Europe, the Americas and the Middle East, as outlined in Table 3.1 from the previous chapter, excluding Ecuador. The data are sourced from Thompson Reuters Datastream, and we follow the mnemonics indexed in (Pukthuanthong and Roll, 2009). The beginning of the sample corresponds to the Asian financial crisis period. Daily returns are generated from price indices for 1 January, 1998 to 15 September, 2017. Global economies endure 10 major crisis periods and several minor turmoils within the sample periods as modelled in Table 3.2, from the previous chapter. Further, we include the West Texas Intermediate index to investigate shocks coming from the oil market and S&P GSCI commodity index to investigate the effect of commodity inclusion.

Taking natural logarithms of the data we transform price to returns data. We further use a two-day moving average filter, removing time zone effects as in Forbes and Rigobon (2002).

Discussions concerning properties of asset returns dominate in both the current and early literature. Among early studies, Fama (1976) suggested that daily asset returns series are more non-Gaussian than are shorter frequency return series. Additionally, Cont (2001) emphasized persistence and non-linearity, while Stărică and Granger (2005) focused more on non-stationarity inherent within stock returns data.

Recently, Joseph et al. (2017) addressed stock returns as non-Gaussian, persistent and time varying, with smooth compact support over low-frequency spectral content. Others suggested that the daily stock returns data are negatively skewed, nonlinear, noisy and volatile (Joseph and Larrain, 2008; Atsalakis and Valavanis, 2009; Joseph et al., 2011; Wollschlager and Schäfer, 2016; Zhong and Enke, 2017). It is crucial to use appropriate filtering and transforming techniques for better detection and decoding of cycles in source data.

Of the relevant studies examining prediction, Zhou et al. (2012) supported on the dissent in theory and practice regarding asset returns. Only the pre-possessing of returns circumvents such misalignment, as suggested by Joseph et al. (2017, 2016); Atsalakis and Valavanis (2009) and Zhong and Enke (2017). A central context of data pre-processing with filtering is, there is no discord in its importance in the relevant studies investigating returns (Joseph et al., 2017).

Finally, Smith (1997) suggested that despite its simplicity as a method, moving average filters do much better in a competitive environment compared to other digital signal processing techniques, such as single pole. Precisely, moving average handles discrete time series in a subtle manner (Smith, 1997).

Within the context of considering raw returns as non-Gaussian, nonlinear, time-variant random data, the importance of spectrum density/frequency domain analysis for pre-processing is undeniable. Hence, moving average is the chosen signal processing technique here. On another note, 'spectral windowing' is important to extract detectable edges and avoid aberrations caused from discontinuity in the raw data. Naturally, the chosen window size is 2 in our paper, which is consistent with (Oppenheim and Schafer, 2014) and (Forbes and Rigobon, 2002).

The transform function

$$\begin{aligned} a\,(1)\,y\,(n) = b\,(1)\,x\,(n) + b\,(2)\,x\,(n-1) + ... + b\,(n_b+1)\,x\,(\eta-\eta_b) \\ -a\,(2)\,y\,(n-1) - \ldots - a\,(\eta_b+1)\,y\,(\eta-\eta_a) \end{aligned} \tag{4.7}$$

handles both infinite and finite impulse responses. The moving average filter derived from the rational transfer function allows input of different window size (ws) $y\,(n) =$

$\frac{1}{\omega s}\left(x\left(n\right)+x\left(n-1\right)+\ldots+x\left(n-\left(\omega s-1\right)\right)\right)$

Indeed, our pre-processed data characterised by the frequency contents of the signals, better detects the periodicity than does the raw unprocessed returns data. Table 4.1 presents a selection of statistics for the 30 return indices; including average, minimum, maximum, standard deviation and Jarque-Bera test results for normality in distribution. The greatest spread between minimum and maximum is found for Venezuela, Kuwait and Iraq, all of which have high standard deviations. As is usual for returns normality is rejected at the 5 per cent significance level. Rather, these indices have more leptokurtic and skewed distributions, consistent with the crisis effects throughout the sample period (Brown and Warner, 1985; Fama and French, 1988; Kim et al., 1991; Corhay and Rad, 1994; Longin, 1996). **In addition to robustness tests with different rolling windows, we have examined the possibility of multicollinearity in residuals.** We found correlation coefficients to be null and insignificant in the residuals, ruling out the possibility of loss of consistency in our estimation outputs.

In the following section, we present a comparison in the estimates gauged from DY, MHD and SVD. Note that, while DY and MHD estimates are computed drawing on data from the complete sample size, the MHD-SVD spread draws on from 5 minute interval prices for September 2009 until September 2017. Due to the limited availability of five-minute interval prices for important South Asian countries, such as Singapore, we trim the data down to fit vector sub-spaces within the specified matrix space, for all other vectors retaining Singapore. For similar reasons, we also remove Middle Eastern markets. We include Mexico in the sample vectors, as it represent an important, emerging oil exporting market.

4.4 Empirical Results

In the current section, we discuss the comparative analyses that Table 4.3 and Table 4.4 provide and figures 1 to 26 produces. A detailed explanation of the amplifying and dampening of transmissions and vulnerability is also described in Table 4.3 and Table 4.4. Hence, in this section, we contrast the results drawn from these tables computed with DY, MHD and SVD methods.

The analysis holds for two fundamental principles. First, a common phenomenon that largely holds is that big transmitters are generally more susceptible to global contagion shocks, and that propagation of crisis with contagion is one directional. Second, in identifying contagion from an aggregate risk assessment, our economic prior is that for the markets in which locally induced volatility swings together with spillover, the increases coming from interconnection amplify the aggregate risk estimates, which reverts the market to a steady state by releasing excess risks onto others. Hence, in times of excess volatility, markets are more epidemic in nature.

Next, we discuss comparisons by market blocks (see Table 4.1): Asian crisis (AC), export crisis (EC), Greek crisis (GC), oil exporting developed (OED) and oil export emerging (OEE).

Table 4.3 and Table 4.4 show that India, Singapore and Thailand in the AC cluster are highly susceptible to their own market shocks, but this holds less so for Malaysia, South Korea and the Philippines. While many past studies have contended (including our DY estimates) that Malaysia and the Philippines are more resilient for not being deeply connected to global networks as others (Raghavan and Dungey, 2015), our MHD estimates further suggest the latter set of markets receive strong shocks in major events. As given in Figure 4.1, Figure 4.6, Figure 4.11, Figure 4.16, Figure 4.21, Figure 4.26, and Table 4.3, Table 4.4, we suggest that the Indian, Malaysian and South Korean markets are more vulnerable to globally induced contagion than are the rest. The transmission estimates uphold this phenomenon by depicting these markets as low transmitters that are highly vulnerable to an epidemic in the holistic network. As Thailand, Singapore and the Philippines remain more susceptible to local volatility, unsurprisingly they emerge as strong transmitters as they release 'excess volatility' to other peripheries (see Table 4.3 and Table 4.4). This 'excess volatility' refers to the accumulation of instantaneous self-exciting stochastic volatility in excess of volatility spillovers coming from the networks itself.

Simultaneous volatility changes in common factors with large scale events often pollute the degree of actual spillovers as suggested in Dungey and Renault (2018). In Table 4.3, Table 4.4 and Figure 4.2, Figure 4.7, Figure 4.12, Figure 4.17, Figure 4.22, Figure 4.26, we identify risks generated out of interconnections in the network from localised volatility changes for the EC (i.e., Germany, Chile, France, China, the UK and Australia) market cluster with MHD-SVD spread. We identify that Germany, Chile and the UK are predominantly more vulnerable to instantaneous transitory spikes in volatility, polluting the actual degree of shocks received from interconnections within the network. Consistent with the principle of high spreaders being less susceptible to vulnerability coming from a global contagion, the UK and France turn out to be high transmitters of crisis, especially during the GFC and eurozone crisis. For Australia, transmissions are triggered strongly with 'excess volatility' and, as such, it is highly vulnerable to epidemic shocks in the network. As opposed to Dungey and Renault (2018), who suggested Germany does not suffer from the same market reassessment risk as major markets and is distanced from other connections, we find Germany and China are highly susceptible to crisis received from other markets with 'excess volatility' most recently. Consequently, this indicates the degree of systemic risk found within these markets is due to contagion. At the onset of the Chinese and export crises, the heightened volatility in the German and Chinese market starts spilling excess risks onto others, resulting in amplified transmission in the network as laid out in the second principle.

In comparing DY and MHD, we find MHD rejects DY's depictions of Germany and France as the highest spreaders of crisis. Despite occasional spikes in resilience responding to major global events spanning our sampling periods, Germany remains more vulnerable to crisis coming from contagion than does France or the UK. While we may attribute the degree of transmissions coming from France as neutral to dampening, the UK is largely a spreader with strong resilience to contagion.

Table 4.3, Table 4.4 and Figure 4.3, Figure 4.8, Figure 4.13, Figure 4.18, Figure 4.23, and Figure 4.26 depict that the GC countries' (i.e., Greece, Portugal, Ireland, Belgium, Croatia and Austria) markets are very sensitive to events contributing to global contagion. These markets are less characterised by local shocks and the shocks generated in the neighbouring nodes, except for Greece and Belgium. However, the MHD measure selects Greece and Austria as becoming more resilient as the eurozone crisis subsides, while Portugal and Ireland becomes more vulnerable. This can be attributed to investments moving out of Greece and Belgium and into Portugal and Ireland, making the latter deeply connected. Moreover, MHD captures Croatia remaining strongly resilient to shocks across the periods spanning our sample, which DY fails to detect.

Our transmission estimates for GC countries and the transmission vulnerability mechanism are in line with what we provided in the first principle. As Portugal becomes more vulnerable to global contagion more recently, it is of no surprise to find that Portugal and Ireland transmit stronger shocks in the past. This suggests Portugal and Ireland remain deeply connected with the other peripheries since before the GFC. Moreover, with dropping vulnerability coupled with 'excess volatility', Croatia emerges as a strong transmitter during the eurozone crisis.

Figure 4.26 shows the volatility jumps unique to Greece and Ireland, in which the excess vulnerability also sets off network transmissions to other markets. In contrast, transmissions emerging from Portugal and Austria that corresponds to excess vulnerability is coming from volatility and, hence, is short-lived. Notably, there is little risk of spillover over-identification for Belgium and Croatia

Table 4.3, Table 4.4 and Figure 4.4, Figure 4.9, Figure 4.14, Figure 4.19, Figure 4.24, and Figure 4.26 concerning OED countries' (i.e., the USA, Canada, Russia, Norway, Japan and New Zealand) markets depicts that stochastic local volatility predominantly affects the vulnerabilities of the USA, Norway and Mexico. In fact, the recent degree of risks stemming from the USA and Russia is emanating mostly from 'excess volatility'. In contrast, exceeding return spillovers following the onset of export crisis for Norway, Japan and New Zealand suggests these markets are especially contagious. The spread falls for Canada and, very recently, for Mexico, suggesting the spillovers in these markets are driven less by local volatility and more by their dominance in the holistic network.

Taking a more granular view with our MHD and DY comparison, the Japanese and New Zealand transmissions provide further reassurance as to the nature of these markets' vulnerabilities. Japanese volatility transmission is depicted as contagion transmission, which corresponds with Japan emerging as a highly connected market out of its long-lasting economic stagnation in early 2000. Neutral to dampening volatility transmissions stemming from the USA, but also a curving up of its transmission swings with a shifting regime, gives credence to BIS (1998) suggestion that both the USA and Japan are 'conduits' for contagion transmission. Conversely, the upheavals in the global oil market influence the nature of New Zealand's contagion, more so than for other global events.

Comparing DY and MHD estimates we further find that, the USA and Japan are more susceptible to contagion risk transmissions than to the degree of risks they transmit themselves. The exaggeration of risk susceptibility is overlain with risks transpiring within, especially for the USA and Japan. Moreover, dismissing what is gauged from DY estimates regarding Russia, MHD substantiates Russian resilience spanning across the entire sample period. Additionally, Russian transmissions pick up in all major events. To a much lesser extent, this holds true for Norway as well.

Finally, turning to OEE countries' (i.e., Saudi Arabia, Israel, Iraq, Kuwait, Nigeria and Venezuela) markets, we conjecture these markets are not at all contagious by examining Table 4.3, Table 4.4 and Figure 4.5, Figure 4.10, Figure 4.15, Figure 4.20, Figure 4.25, Figure 4.26. Although the countries in this cluster dominate the global oil market, an upheaval in the oil market increases the market strength in these markets.Consequently, they demonstrate strong resilience in phases of price or supply shocks in the oil market.

In several occasions for the OEE cluster, DY estimates fail to produce convincing evidence that aligns with MHD. DY fails to capture the amplifications in vulnerability for Saudi Arabia corresponding to the advent of the GFC and the diminishing systemic risks emitting from Iraq. MHD captures this successfully. Further, more recently, DY fails to capture the increases in vulnerability for Venezuela, which is more sensible given the heightening of the Venezuelan economic crisis, but is depicted in the MHD curves. With MHD, we disentangle the spikes in volatility transmissions for Kuwait, which naturally responds to the Iraq invasion and oil supply shock. In both cases, confidence build-up occurs dramatically in the Kuwait market. Again, DY fails to capture the dampening of Nigerian systemic risk transmission with the oil price crash following the Iraq invasion. On balance, we sufficiently provide evidence of MHD better capturing larger effects on the economy than DY.

4.4.1 Identifying contagion

A key contribution of the current paper is 'contagion' identification in the pool of markets from interconnection, for which crisis demarcation is not a necessary condition. While all interconnections and amplifications in the systemic risk that is found within this sample markets do not lead to contagion, contagion poses the unique threat of a financial pandemic. Hence, contagion is a necessary condition for a widespread crisis to ensue. We propose a tractable and simple technique to identify contagious markets while the condition remains dynamic. Thus, a key question at this stage is, 'How diabolic is a contagious market today compared to in the past?' In other words, are we going to experience a global meltdown similar to that of the GFC if a crisis is triggered from a contagious market?

From Figure 4.26, we separate out Singapore, China, Australia and Japan as more contagious markets than the rest, especially in mor recent times. Despite observing that the 2016 Chinese stock market crash sends shocks tumbling globally, the carnage is not as pronounced as in the GFC.

The models presented here shows that the Chinese stock market crash unfolding in January 2016 sets off a global rout, dragging down the stocks across the USA, Germany and rest of Europe and Brazil to 2 to 3 per cent. Chinese economic growth plunges to 25-year low. Leading up to this, speculations and warnings reflected engendered fears of a global meltdown, including warnings issued by the International Monetary Fund (Mauldin, 2017; Liang, 2016; Mao, 2009; Elliott, 2017; Cheng, 2017). The Chinese authority responded by imposing new trading curbs and devaluing currency. While commentators, including the China Securities Regulatory Commission blamed surging speculation and irrational investment behaviour for sourcing the crisis, Mao (2009) suggested that the colossal shadow banking industry was responsible for heightening the risks in the Chinese markets much earlier. Presumably, potential risks are predominant in the shadow banks in China, which have quadrupled at an annual rate of 34 per cent since 2008, and at that time the size of the Chinese shadow banks (US $8 trillion) is equal to 4.3 per cent of Chinese (Mao, 2009). Liang (2016) asserted that the burgeoning shadow economy, amidst the goal of boosting productivity against an overall drop in the labour market, posed a high risk to the financial stability of China given its current regulatory framework.

We do not experience a replay of the 2008 GFC. Recently, Dungey et al. (2020)provided evidence of no new systemic crises emerging from China to other global markets given the resurgence in systemic risk. While our study purports to identify sources of crisis, the case for China is particularly interesting. Generally, the results capture a unique case of shadow banking and securitisation. There is a plethora of studies showing bank securitisation leads to higher systemic risks, while increasing bank profitability and ensuring a buffer of liquidity for the bank (Adrian and Shin, 2009; Uhde and Michalak, 2010; Nijskens and Wagner, 2011; Nadauld and Weisbach, 2012; Georg, 2013; Battaglia et al., 2014; Bakoush et al., 2019b). Although securitisation allows banks to shed their own idiosyncratic risks into financial markets and confirms a buffer of liquid assets coupled with higher profitability, a vicious cycle forms as banks' exposure to credit risk intensifies. The shadow banking industry is evolving to retain risks while pursuing regulatory arbitrage by means of retaining rollover risks pertaining to maturity mismatch. These pose a significant threat for the sponsors assuming these risks. In effect, conduits are attributed with systemic risk involving commercial banks, insurance institutions and equity market components. This also explains the USA or other advanced markets posing no significantly new threat in recent times, partly because the post-2008 credit crisis saw several restrictions imposed on banking securitisation, particularly in advanced economies. The Association for Financial Markets in Europe (2017) reported a significant reduction in securitisation activities within 10 years, especially for the USA and European banks. Evidently, this has impaired the capital and profitability of these banks, as suggested by the Bank for International

Settlement (2018).

Moreover, we do not observe a re-emergence of global meltdown from China or other contagious markets because of the structural differences between cross-border capital diffusion to what was occurring with the USA during the GFC. Shirai and Sugandi (2018) reported that Hong Kong, Japan and Singapore are the major financiers of cross-border capital in the Asia–Pacific economies. While Singapore has the largest financial centres and is also the largest equity investor to the People's Republic of China (PRC), Japan, Republic of Korea (ROK), and others in the Association of Southeast Asian Nations, Japan invests largely in Australian debt securities. Conversely, Hong Kong invests mostly in the equities issued by the PRC.

Issuing US$3.5 trillion cross-border portfolio assets, Japan's exposure to the Asia–Pacific region is mostly through Australia (US$572 billion), and vice versa. Despite this, the Asian Bond Funds administered and managed by banks for international settlement exclude Australia, Japan and New Zealand. The Asian Bond Funds ABF1 and ABF2 were introduced to develop the sovereign and quasi-sovereign bond markets dominated by the USA dollar and local markets, respectively. However, these countries are the main pathway for the USA and EU to invest in the region. Hence, 60 per cent of the total shares issued in the USA and EU forms the cross-border portfolio for Japan, Australia and the ROK in the region establishing a strong bridge between the continents. Singapore is the largest investor in shares issued by the USA and EU. While the cross-border portfolio assets of Hong Kong, China, sum up to US$1.1 trillion, its portfolio shares mostly concentrate on the PRC (50 per cent) followed by the Association of Southeast Asian Nations-5 (37 per cent). The USA and EU shares constitute only 24 per cent of the cross-border portfolio trading in Hong Kong, China. Hong Kong invests US$404 billion in the PRC-issued shares, compared with US$235 billion by Japan and US$218 billion by Singapore. Hong Kong has only US$99 billion invested in USA assets and US$165 billion invested in EU assets. In contrast, Australian foreign assets include 42 per cent USA-issued securities, with only 26 per cent from the EU (Shirai and Sugandi, 2018).

In terms of cross-border portfolio liabilities, 73 per cent of Japan's total cross-border portfolio liabilities (US$1.7 trillion) are financed by the USA and EU, while the USA and EU finances 33 per cent and 29 per cent, respectively, of total liabilities of Australia (US$966 billion). Interestingly, while the USA and EU finances 66 per cent of the total cross-border portfolio liabilities of Hong Kong (US$390 billion), Hong Kong finances 42 per cent of the total liabilities of the PRC (US$710 billion). As a net debtor of cross-border portfolio investments to the world, Australia remains highly exposed to the USA and EU, which account for over 70 per cent. Since 2001, For Japan, Australia also remains its biggest investment destination, increasing investing into Australia by four times (US$118 billion) in the post-GFC. The foreign portfolio asset and liabilities of Hong Kong and Singapore exceed that of Japan in the post-GFC, and for Hong Kong these grow by 157 per cent and 142 per cent, respectively (Shirai and Sugandi, 2018).

In summary, as highly contagious markets, Japan and Singapore are not causing widespread crisis, as no crisis is revealed in these markets, or in the USA or EU in more recent times. In fact, the restrictions applied in the USA securitisation induce calmness in these markets. Hence, we are also observing calmness in the Australian markets. However, given the degree of exposure to each other and connectivity between these markets, a large enough shock in any of these markets may destabilise the other. In contrast, Hong Kong, China, concentrates investments mostly in the PRC. As both the economies are part of the PRC, this creates a closed-circuit transmitting wealth within. This is also a reason why the 2016 crash was absorbed mostly within the circuit and did not turn diabolical, despite having all the potential. In fact, this allows the central Chinese authorities to apply new restrictions, such as short selling bans or bans on stock investments as appeared in 2015, without inciting a global response.

4.5 Conclusion

In this paper, we have identified contagious and more volatile markets relying on time-varying systemic risk in an associated network of markets. We began by exploring the transmission of risks and vulnerability to risks spanning across the sample period of nearly 20 years with unsigned return measures (DY), a well-known method proposed by Diebold and Yilmaz (2012). Next, we estimated return spillovers with signed spillover measures computed with signed historic decomposition proposed recently by Dungey et al. (2018b), and concluded that signed spillover measures capture all or more information than DY spillover measures. Third, we estimated signed volatility transmissions and vulnerabilities computing from MHD, and drew on realised variances from five-minute intraday returns. Finally, we plotted the differences between time-varying volatility and return spillover estimates, which showed the markets that are epidemic in the complex network structure and the markets that are endemic in nature but predominantly volatile with a higher core volatility. Hence, we have addressed the issue of over-identification in the degree of systemic risk, which the markets emit in calm and crisis periods.

We found that mis-identification of contagion issues is prevalent when explaining risk transmissions and the build-up of market resilience across time with the DY spillover method only. We addressed these issues by re-estimating systemic risks with MHD. In the absolute representation of time-varying DY spillover measure, we found that DY spillover overestimates the level of actual resilience building for South Korea, the Philippines, Singapore, Germany, China and Israel. This measure also overestimates the degree of risk transmissions coming from Iraq, Venezuela, the USA (prior to the GFC) and, more recently, Nigeria and Greece. While the DY underestimates Greek, Croatian and Russian resilience building in recent years, it also underestimates the risks emanating from Kuwait, South Korea and Germany. Severe changes in market micro-structure corresponding to profound economic degradation is rather misrepresented as resilience building with DY for its absolute representation of spillovers. We found this holds for both Iraq and Venezuela. The signed spillover estimates captures the convergence in the swings of systemic risks as the economies in both the countries collapse.

We addressed a crucial phenomenon as we separated out the influence of stochastic local volatility as opposed to the actual degree of systemic risks found within a market. First, a market is not likely to be transmitting shocks and remain vulnerable at the same time. Moreover, during high-risk transmissions, markets turn more resilient or vice versa. However, it is more likely that high transmissions lead to a phenomenal increase in vulnerability for the market to negative in-shocks transpiring within the network. Second, in the amplification of total risk generation with the accumulation of self-exciting intraday local volatility added to systemic risks coming from the network, markets respond by casting off 'excess volatility' onto others. In other words, it is likely that a highly volatile market gives strong episodes of risk transmission at the start of an event without becoming an epidemic market. Nevertheless, such spikes may accompany a fall in the local market, as outlined in Bates et al. (2019).

Complementing the work of Dungey and Renault (2018), our technique identified the degree of systemic risks free of simultaneous volatility increases accompanying a rise in volatility in common factors, and may have various contributions to the field of economics and machine learning. First, it may enable managers of risk to better rebalance portfolios, parsing information concerning epidemic and non-epidemic elements in the portfolio. Supervisors may find it useful to understand risks coming with big links, and to target issues amplifying risks. Machine-learning enthusiasts may find it interesting to feed forward networks of markets scaled with proper degrees of systemic risk indices. Further, Bayesian priors can be generated weighted with amplifications and dampening in signed risk estimates, and predictability of market risks can be improved. In all, the methods combined not only serve a purpose by producing comparisons, but produces better information regarding a market's susceptibility to realised crashes and volatility evolution.

We attempted to explore complex market associations spanning across the last two decades, encapsulating major global events across many markets. The markets were selected to represent dynamic shifts that each subsequent event provides and were then grouped into a closed system. As with the precursors of systemic risk studies, limitations arose from the limited intraday data availability for the Middle Eastern markets. However, we substituted with additional markets that depicted a similar pattern. Alternatively, a target should be an investor sentiment analysis corresponding to risk patterns, leading to a better understanding of strong amplifications in risk propagation.

In the next chapter, we develop a means of visualising the vulnerability of complex systems of financial interactions. These vulnerabilities result from the changing risk tolerance of investors constructing these complex systems, contributing to the build-up of vulnerability in crisis and calm periods. We show how both time-varying risk tolerance and spillover indices can be translated into two-dimensional information transmission and crisis transmission maps, respectively. Taken together, the information transmission maps have the advantage of proposing predictions to potential crisis transmission pathways in the crisis transmission maps.

4.6 Figures & Taables

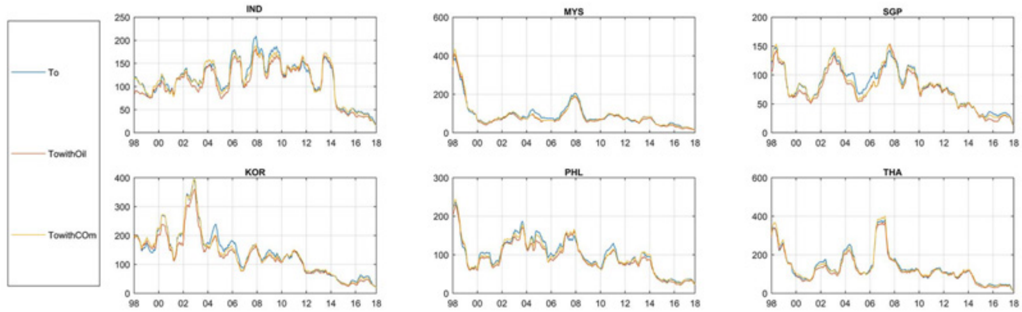


Figure 4.1: DY: Transmission - Asian crisis markets. Note: This figure represents the transmission of systemic risk from the Asian crisis markets to all others, derived from the DY conditional variance index.

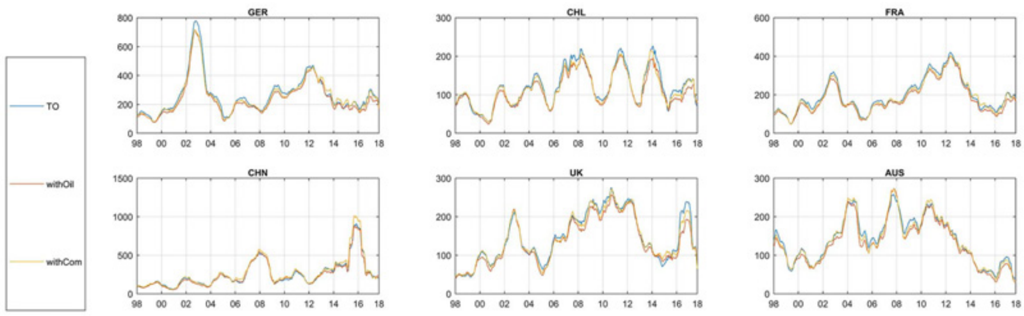


Figure 4.2: DY: Transmission - export crisis markets. Note: This figure represents transmission of systemic risk from Export Crisis markets to all others, derived from DY conditional variance index.

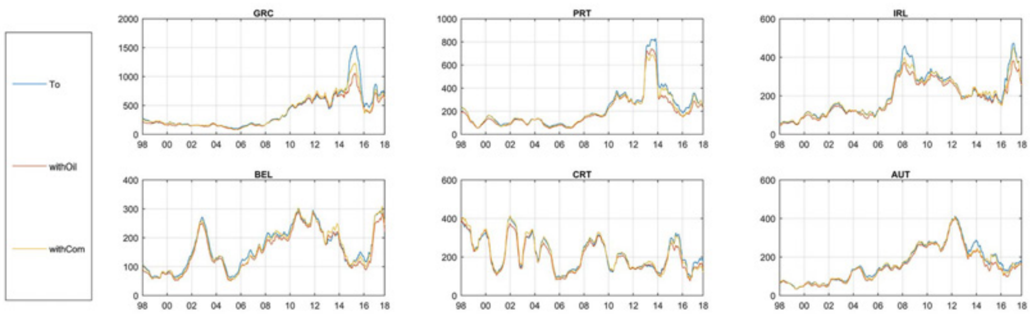


Figure 4.3: DY: Transmission - Greek crisis markets. Note: This figure represents the transmission of systemic risk from the Greek crisis markets to all others, derived from the DY conditional variance index.

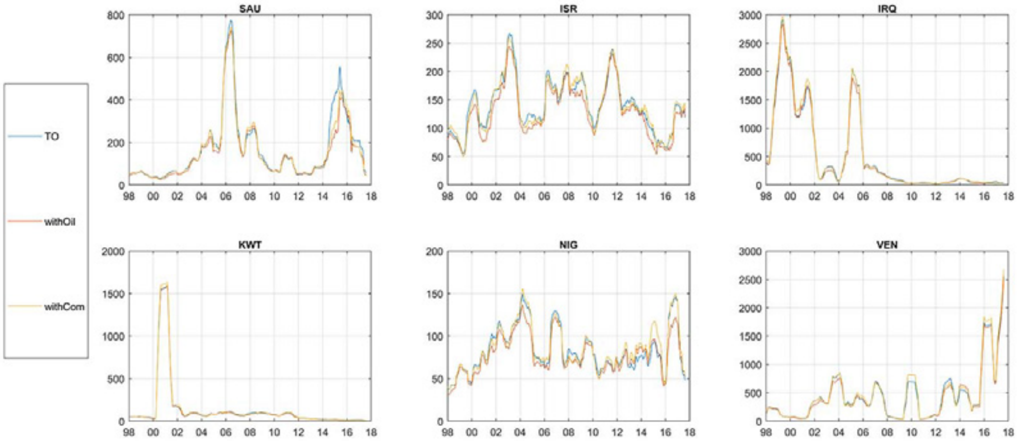


Figure 4.4: DY: Transmission - oil exporting emerging markets. Note: This figure represents the transmission of systemic risk from major oil exporting emerging countries' markets to all others, derived from the DY conditional variance index.

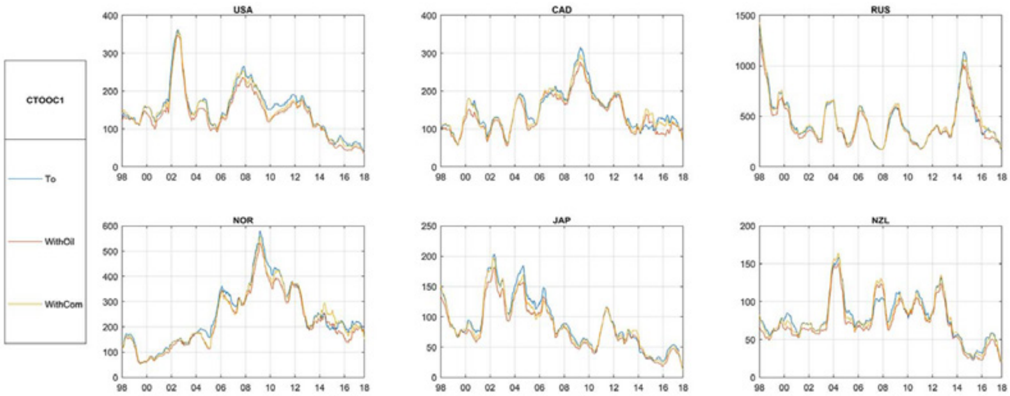


Figure 4.5: DY: Transmission - Oil exporting developed markets. Note: This figure represents the transmission of systemic risk from major oil exporting developed countries' markets to all others, derived from the DY conditional variance index.

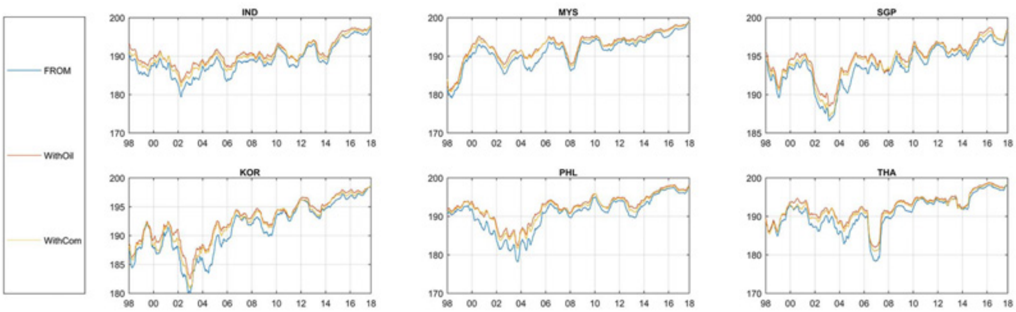


Figure 4.6: DY: Vulnerability - Asian crisis markets. Note: This figure represents the vulnerability of Asian crisis countries' markets to systemic risk transmitted from other markets to own markets , derived from the DY conditional variance analysis.

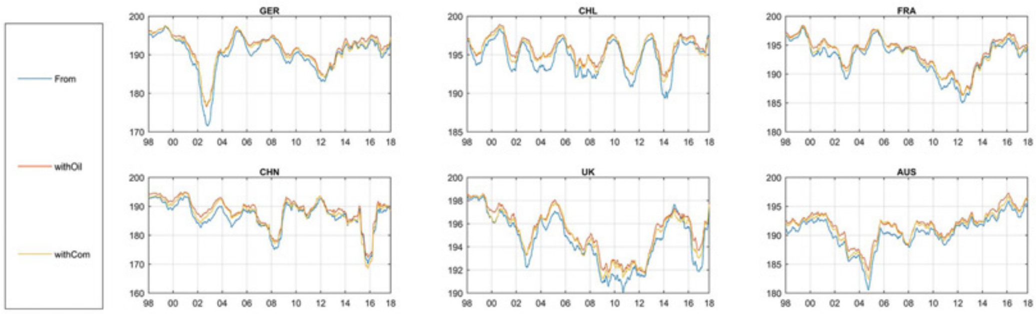


Figure 4.7: DY: Vulnerability - export crisis markets. Note: This figure represents the vulnerability of export crisis countries' markets to systemic risk transmitted from other markets to own markets , derived from the DY conditional variance analysis.

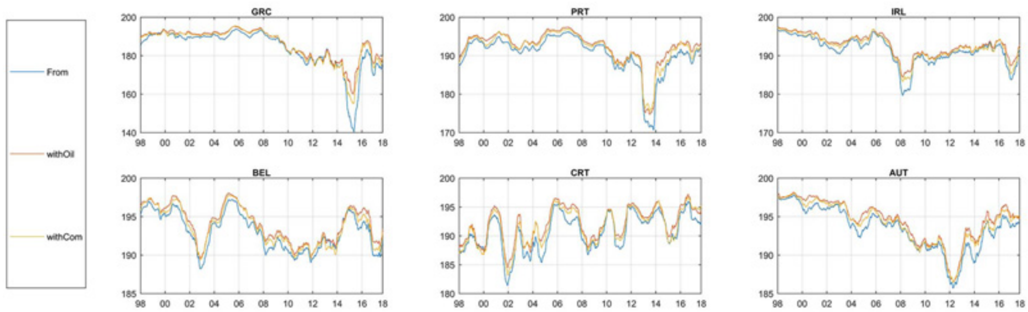


Figure 4.8: DY: Vulnerability - Greek crisis markets. Note: This figure represents the vulnerability of Greek crisis countries' markets to systemic risk transmitted from other markets to own markets , derived from the DY conditional variance analysis.

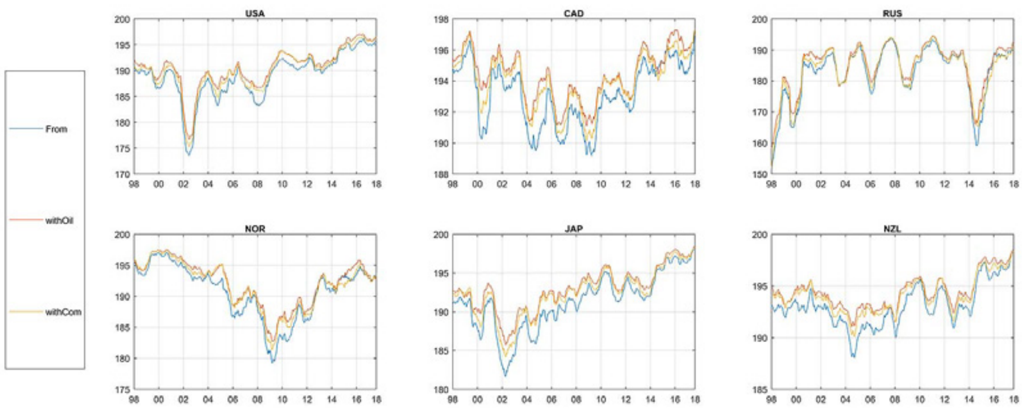


Figure 4.9: DY: Vulnerability - oil exporting developed countries' markets. Note: This figure represents the vulnerability of major oil Exporting developed countries' markets to systemic risk transmitted from other markets to own markets , derived from the DY conditional variance analysis.

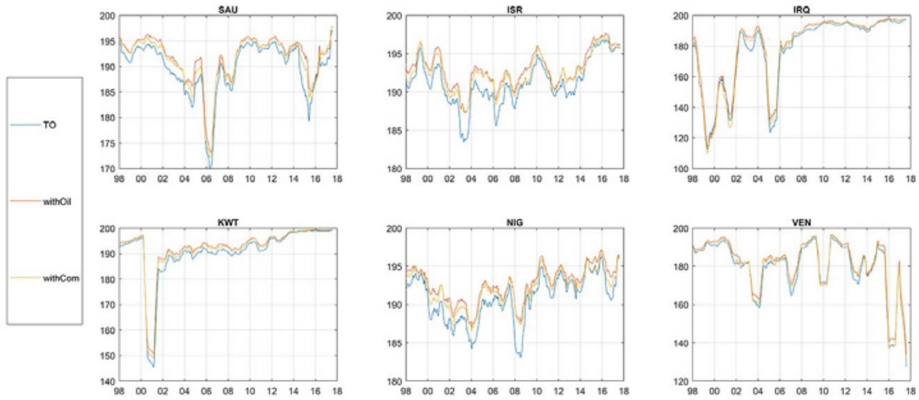


Figure 4.10: DY: Vulnerability - oil exporting emerging countries' markets. Note: This figure represents the vulnerability of major oil Exporting emerging countries' markets to systemic risk transmitted from other markets to own markets, derived from the DY conditional variance analysis.

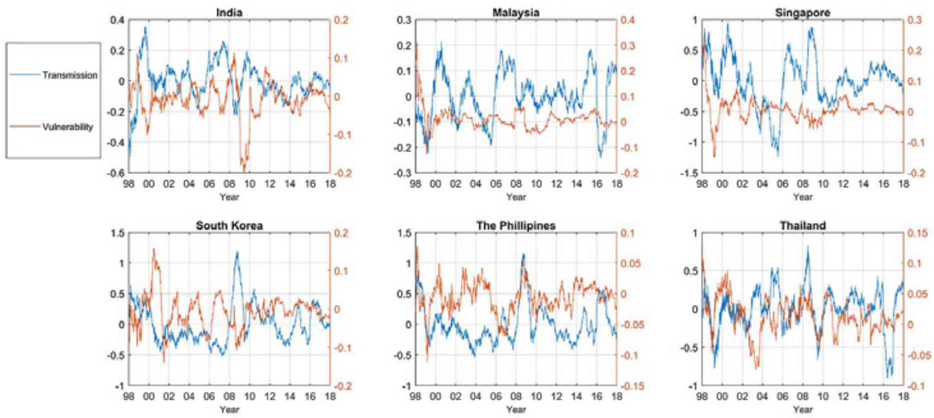


Figure 4.11: MHD: Asian crisis markets. Note: This figure shows the signed spillover indices of both the transmission and vulnerability of Asian crisis countries' markets, to and from all other markets, respectively.

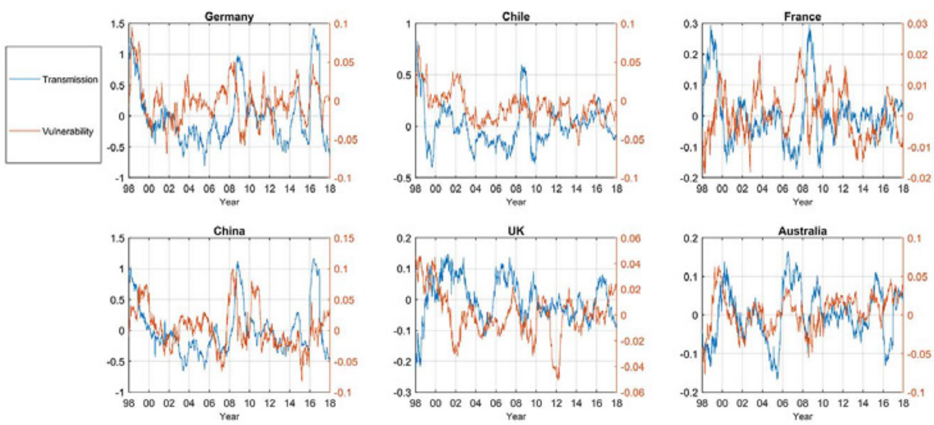


Figure 4.12: MHD: export crisis markets. Note: This figure shows the signed spillover indices of both the transmission and vulnerability of export crisis countries' markets, to and from all other markets, respectively.

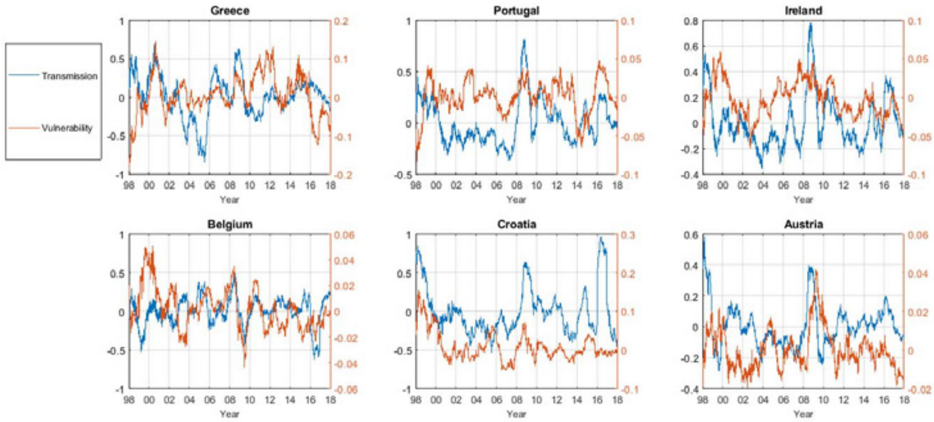


Figure 4.13: MHD: Greek crisis markets. Note: This figure shows the signed spillover indices of both the transmission and vulnerability of Greek crisis countries' markets, to and from all other markets, respectively.

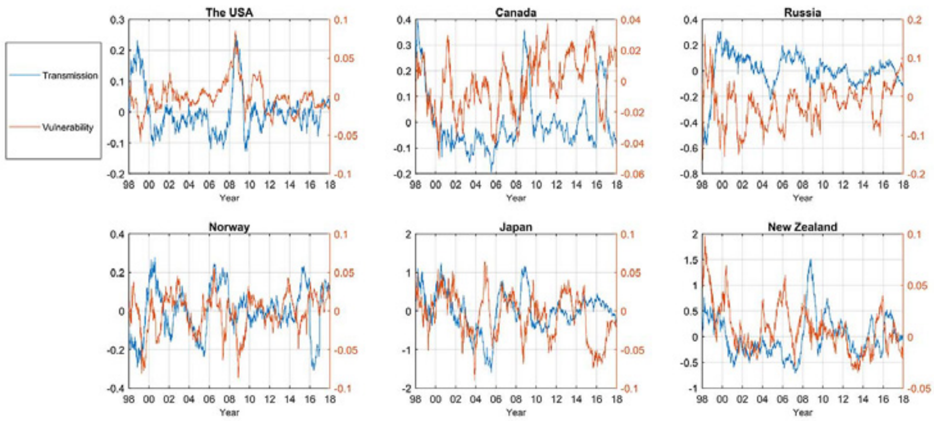


Figure 4.14: MHD: oil exporting developed countries markets. Note: This figure shows the signed spillover indices of both the transmission and vulnerability of oil exporting developed countries' markets, to and from all other markets, respectively.

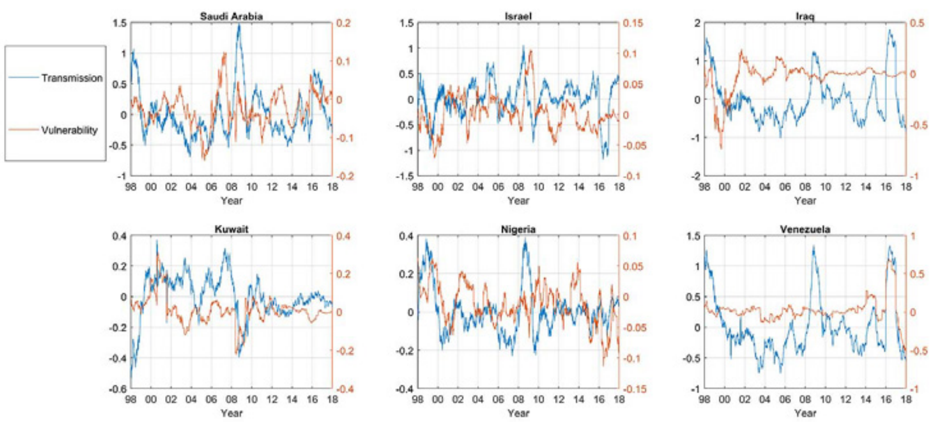


Figure 4.15: MHD: oil exporting emerging countries' markets. Note: This figure shows the signed spillover indices of both the transmission and vulnerability of oil exporting emerging countries' markets, to and from all other markets, respectively.

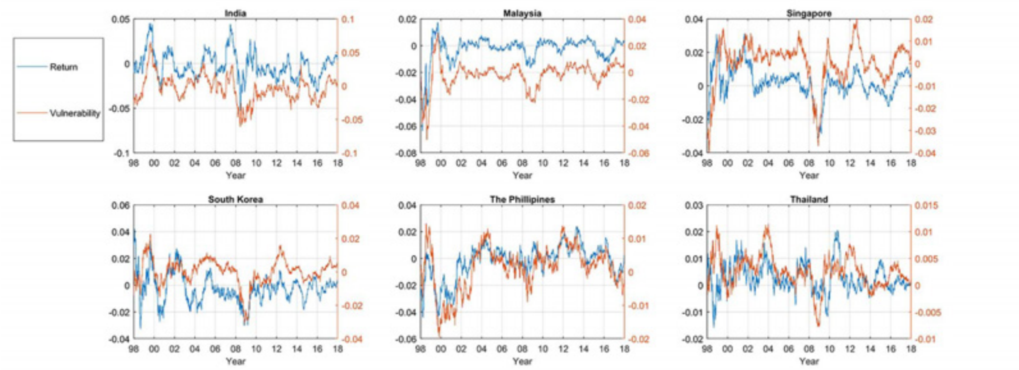


Figure 4.16: MHD and SVD vulnerabilities: Asian crisis market. Note: This figure shows the signs of in-shocks sourced from the Asian crisis countries' markets to targets listed in the AC cluster gauged in signed spillover index and the signed volatility index .

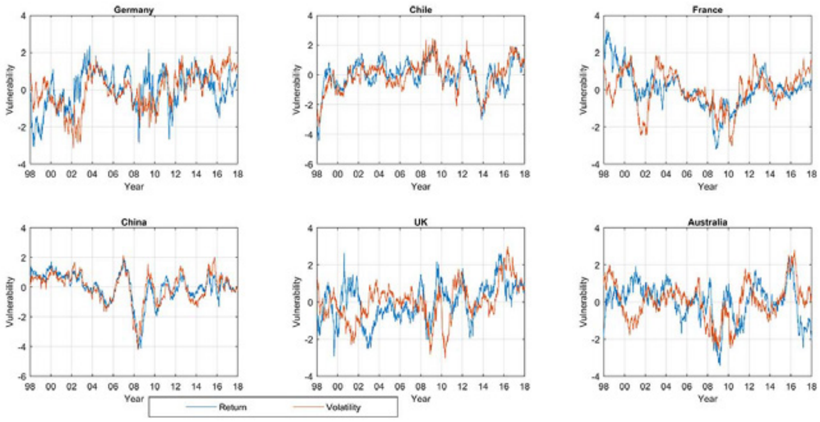


Figure 4.17: MHD and SVD vulnerabilities: export crisis market. Note: This figure shows the signs of in-shocks sourced from export crisis countries' markets targets listed in the EC cluster gauged in signed spillover index and the signed volatility index.

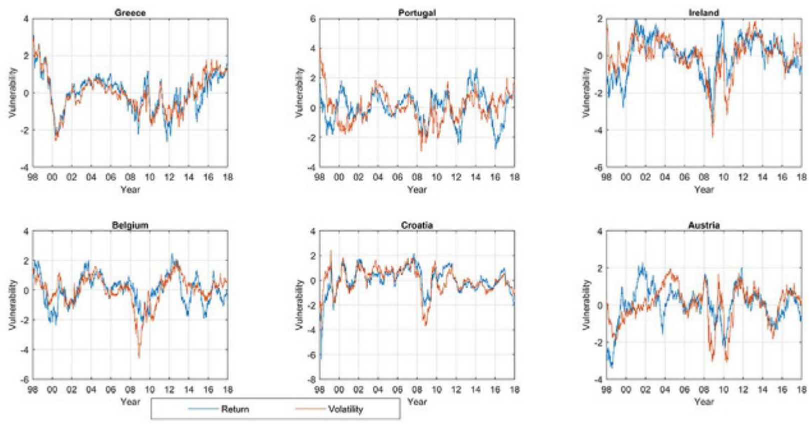


Figure 4.18: MHD and SVD vulnerabilities: Greek crisis market. Note: This figure shows the signs of in-shocks sourced from Greek crisis countries' markets targets listed in the GC cluster gauged in signed spillover index and the signed volatility index.

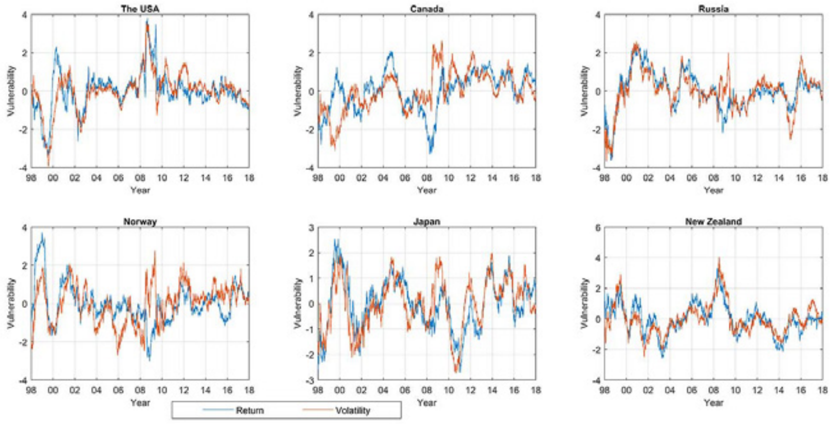


Figure 4.19: MHD and SVD vulnerabilities: oil Exporting developed countries' markets. Note: This figure gives signs of in-shocks sourced from oil exporting developed countries' markets targets listed in OED cluster gauged in signed spillover index and signed volatility index .

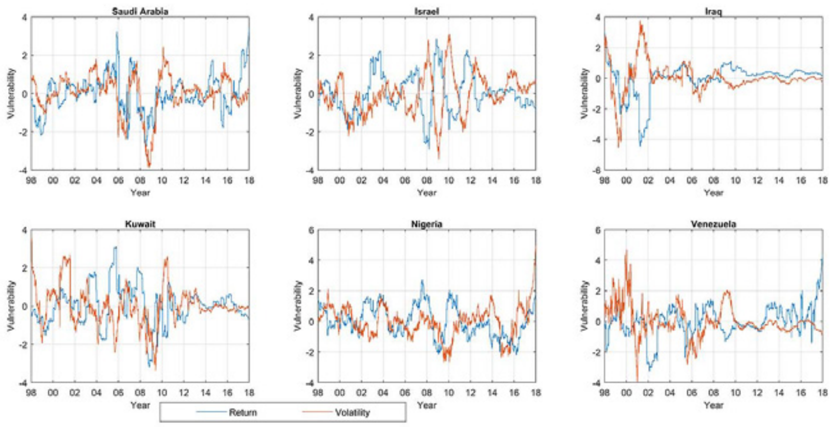


Figure 4.20: MHD and SVD vulnerabilities: oil exporting emerging countries' markets. Note: This figure shows the signs of in-shocks sourced from oil exporting emerging countries' markets targets listed in the OEE cluster gauged in signed spillover index and the signed volatility index ..

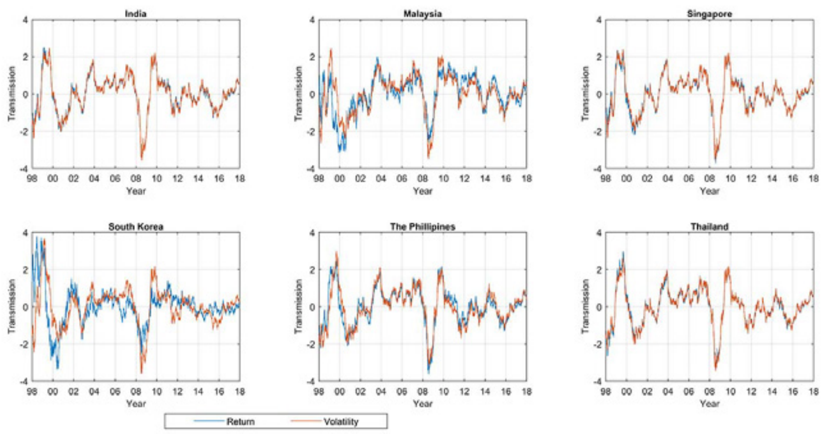


Figure 4.21: MHD and SVD transmission: Asian crisis countries' markets. Note: This figure shows the effects of out-shocks sourced from Asian crisis countries' markets to recipients listed in the AC cluster gauged in signed spillover index and the signed volatility index .

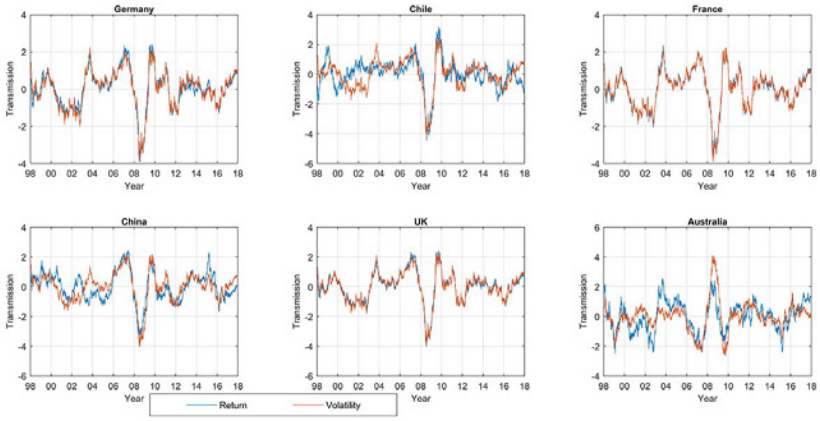


Figure 4.22: MHD and SVD transmission: export crisis countries' markets. Note: This figure shows the effects of out-shocks sourced from Export crisis countries' markets to recipients listed in the EC cluster gauged in signed spillover index and the signed volatility index .

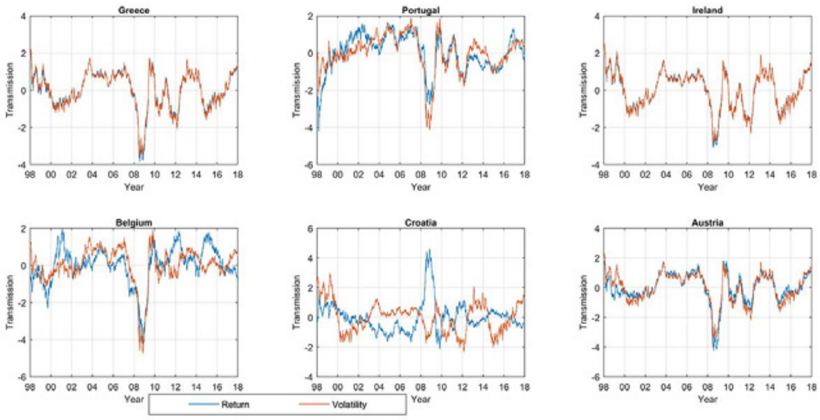


Figure 4.23: MHD and SVD transmission: Greek crisis countries' markets. Note: This figure shows the effects of out-shocks sourced from Greek crisis countries' markets to recipients listed in the GC cluster gauged in signed spillover index and the signed volatility index .

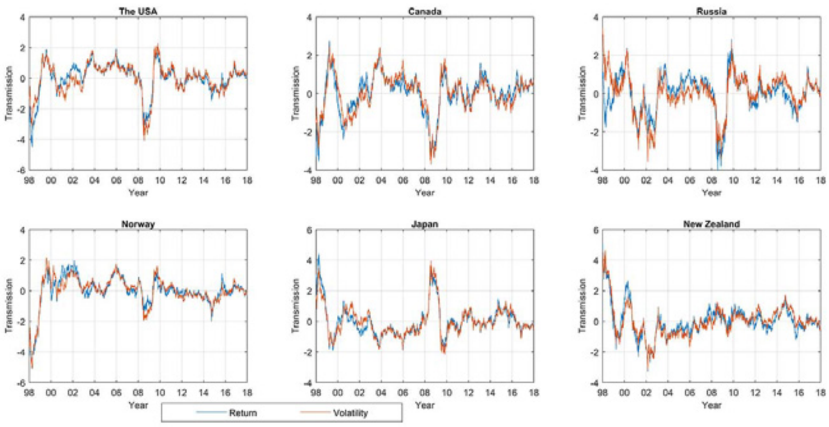


Figure 4.24: MHD and SVD transmission: oil exporting developed countries' markets. Note: This figure shows the effects of out-shocks sourced from oil exporting developed countries' markets to the recipients listed in OED cluster gauged in signed spillover index and the signed volatility index .

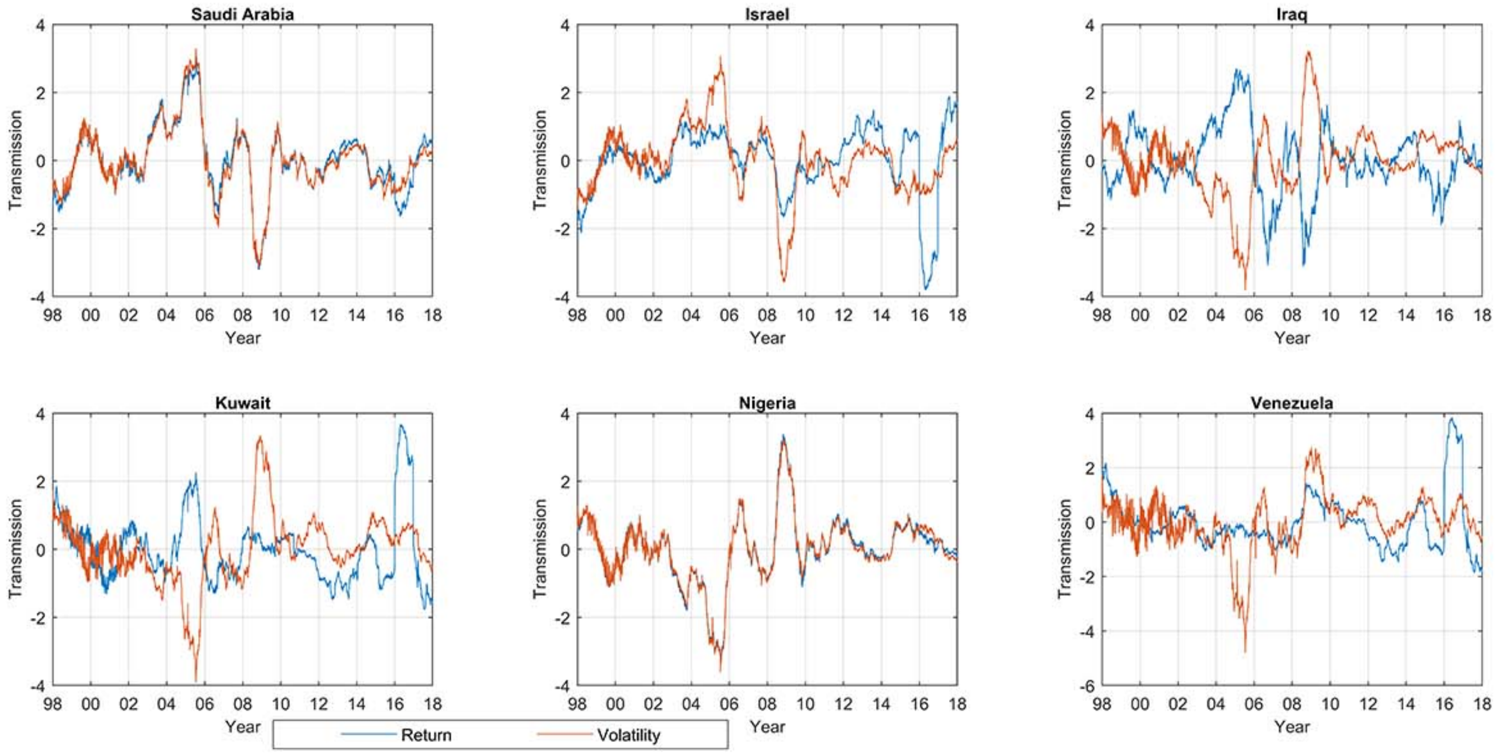


Figure 4.25: MHD and SVD transmission: oil exporting emerging countries' markets. Note: This figure shows the effects of out-shocks sourced from oil Exporting emerging countries' markets to recipients listed in the OEE cluster gauged in signed spillover index and the signed volatility index .

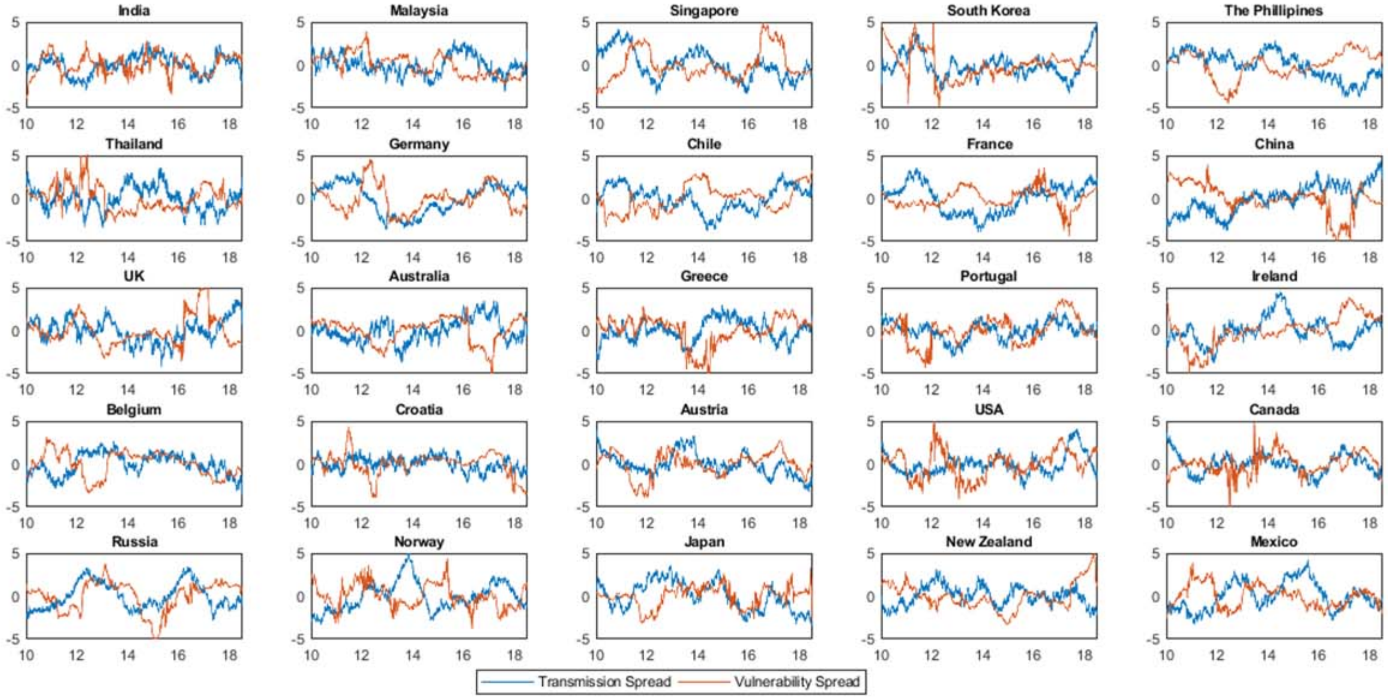


Figure 4.26: The SVD-MHD spread: This SVD-MHD spread figure focuses out contagious markets from non-contagious markets by drawing on estimated differences between the MHD and SVD gauges.

Table 4.1: Descriptive Statistics

Descriptive Statistics	USA	AUS	IND	JAP	MYS	NZL	SGP
Min	-6.629	-8.364	-9.852	-8.239	-19.017	-5.406	-8.848
Max	6.202	8.107	10.783	6.618	17.587	5.138	8.071
Median	0.049	0.069	0.106	0.037	0.022	0.062	0.047
Mean	0.018	0.021	0.038	0.009	0.019	0.017	0.026
Standard Deviation	0.817	1.026	1.244	0.965	1.105	0.832	0.993
JB test p Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Critical Value	5.951	6.008	6.043	6.015	5.986	5.992	5.983
	PHL	KOR	SLK	THA	NIG	VEN	KWT
Min	-8.23	-12.50	-9.95	-10.25	-17.09	-145.75	-62.81
Max	13.890	12.320	11.797	15.888	6.777	20.320	62.554
Median	0.044	0.000	0.000	0.029	0.000	0.008	0.0043
Mean	0.024	0.044	0.025	0.034	0.007	-0.003	0.012
Standard Deviation	1.181	1.514	0.858	1.321	1.129	3.557	1.871
JB test p Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Critical Value	6.019	5.975	5.987	5.988	6.005	5.995	5.996
	IRQ	SAU	CHN	ISR	CAD	GRC	PRT
Min	-41.219	-10.573	-7.863	-6.253	-9.432	-10.350	-7.060
Max	40.780	7.914	6.493	6.506	7.828	8.331	7.494
Median	0.000	0.008	0.020	0.063	0.084	0.064	0.039
Mean	0.027	0.022	0.036	0.028	0.019	-0.012	-0.008
Standard Deviation	2.508	1.013	1.243	0.986	0.985	1.523	1.041
JB test p Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Critical Value	6.003	5.948	6.010	5.996	6.012	5.964	5.986

Table 4.2: Descriptive Statistics

Descriptive Statistics	IRL	BEL	CRT	AUT	RUS	NOR	GER	CHL	UK	FRA
Min	-11.5	-6.9	-11.2	-7.5	-16.8	-10.8	-6.7	-6.2	-9.7	-6.9
Max	5.9	5.8	11.6	8.19	13.8	7.3	7.1	8.3	7.1	6.7
Median	0.07	0.05	0.03	0.07	0.06	0.07	0.07	0.05	0.04	0.07
Mean	0.01	0.02	0.01	0.02	0.021	0.016	0.02	0.03	0.01	0.02
Standard Deviation	1.06	0.95	1.16	1.01	1.809	1.258	1.14	0.82	0.94	1.02
JB test p Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Critical Value	5.98	6.02	5.96	5.97	5.97	6.03	6.03	5.94	5.95	6.0

Table 4.3: Empirical Analysis comparing DY, MHD, SVD

Vulnerability			
Blocks	DY	MHD	MHD-SVD
AC	**1**. India, Malaysia and Thailand show consistently slow increase in vulnerability across the years. **2**. We see dramatic resilience building for Singapore, South Korea and the Philippines, corresponding to that of the USA with the arrival of the Iraq invasion while the USA recovery from dot-com bubble also remains a more conspicuous factor. The general buoyance in the Asian markets resonates with the recoupling in the USA market coupled with expectations soaring with the invasion. Soon after, vulnerability starts rising for the aforementioned countries' markets.	**1**. India, Malaysia and Thailand show lasting resilience across the years spanned by our sample, except for pronounced rises only for India and Thailand in the GFC. Moreover, sheer resilience for India is depicted in 4.6 in the period following the GFC. Among others, Thailand remains somewhat vulnerable, with little spikes in vulnerability corresponding to major events such as the GFC and eurozone crisis. **2**. In contrast to the findings with DY, we do not see resilience building up dramatically for South Korea, the Philippines and Singapore. Indeed, profound amplifications and dampening are depicted in the South Korean and Philippines markets, adding up to what seems like big jumps in the absolute representation of DY. Rather, we find vulnerability to be the more conspicuous factor attributable to South Korea and the Philippines markets. Attributed with a high degree of systemic risk, both these markets' vulnerabilities amplify in response to almost all the major events presented in 3.2. Despite remaining mostly vulnerable, the degree of vulnerability and resilience reverts to the mean degree for Singapore following the post-Asian financial crisis period.	Coming to the identification of small contemporaneous shocks spawning from volatility characteristics of a market, out of mutually reinforcing long-lived correlations, we find India, Singapore and the Philippines are predominantly volatile. Strong inter-temporal volatility contributing mostly to vulnerability predominates for India, Singapore and the Philippines. While sheer resilience for the Philippines during the eurozone crisis is depicted in Figure 4.16, this cannot be held true for the others. However, vulnerability for Malaysia, Thailand and, more recently, for South Korea is coming from far less volatility than are Singapore and the Philippines. This suggests that the former countries are more susceptible to international contagion than to local shocks.

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Table 4.3: Empirical Analysis comparing DY, MHD, SVD

	Vulnerability		
Blocks	DY	MHD	MHD-SVD
EC	**1**. A strong resilience building up for Germany in late 2002 is consistent with the USA, Singapore, South Korea and Japan. This period marks the recovery of the USA and Japanese markets from economic downturns. This period also marks the advent of the Iraq invasion, which rekindled confidence in the energy stocks. For Germany, the sheer resilience is followed by a pronounced drop following the Iraq invasion. Aggregate vulnerability increases with exogenous shocks coming from oil and commodity indices. This observation holds true for other EC markets such as the UK, France, Chile and China. Australian resilience starts to pick up in the Iraq Invasion period. Predominantly a major exporter of energy resources, Australian resilience build-up can arguably be attributable to the tightening of oil supply from the OPEC countries following the Iraq invasion, boosting confidence in Australian commodities market. **2**. Germany, the UK and France are conceivable as potent crisis spreaders as the eurozone crisis unfolds. Consequently, they show strong resilience build-up during the same period. Among others, with the announcement of Brexit, the UK sees resilience picking up again. Resilience also picks up strongly for China as the market recovers, followed by a strong recoupling phase. **3**. Chile remains vulnerable, with vulnerability accelerating more in recent periods corresponding to oil and commodity inclusion, than previously.	**1**. Resilience amplifications are mounting for Germany with DY, but less so with MHD. However, unlike DY, MHD captures the German market remaining vulnerable across most of the sample period, with occasional resilience build-up phases around the GFC and eurozone crisis. Hence, more phases of resilience are identifiable with MHD for Germany. Similar observations accord well with the France vulnerability pattern. The UK market remains strongly resilient, spanning across the entire sample period. In accordance with DY findings, the MHD plot for the UK in Figure 4.12 depicts strong resilience in the post-GFC and during the eurozone crisis. While remaining a strong spreader and being susceptible to shocks during the GFC as held by the global literature, it is indeed promising that the degree of rebounding in the UK market complements recoupling. **2**. Chinese market remains largely vulnerable as depicted in 4.12. A short-lived resilience during the recent Russian crisis is followed only by more periods of vulnerability for China, with the onset of the Chinese stock market crash. MHD finds Chinese vulnerability is repeated across major global events, providing a better rationalisation for the Chinese market mechanism than for DY. Mostly, DY could not detect the cycles of amplification and dampening corresponding to many past events. **3**. Similar to the DY vulnerability pattern for Australia, MHD also suggests Australia remains vulnerable in the years spanned by our sample. This holds true also for Chile.	Contemporaneous small shocks that builds up temporal interdependence corresponding to unprecedented local events rather than long-term interdependence is prevalent in Germany, Chile and France. In other words, the market vulnerabilities of Germany, Chile and the UK are less determined by contagion as outlined in the work of Dungey and Renault (2018). Moreover, we concur with Dungey and Renault (2018) in regards to Germany not suffering from the same market reassessment of default risk as the others. Such can be also be held true for France. Although we find strong volatility spikes contributing to aggregate vulnerability for Germany and China during the eurozone crisis and for the UK in the export crisis (see Table 3.2), return spillovers prevailing for France, Australia and China since the export crisis indicate that these markets' degree of susceptibility increases with contagion within the network itself. Therefore, little decoupling can be expected for these markets and as an economic prior only strong shifts in the network structure may drift the markets away from their current degree of impulses into vulnerability.

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Table 4.3: Empirical Analysis comparing DY, MHD, SVD

	Vulnerability		
Blocks	DY	MHD	MHD-SVD
GC	**1**. Greece, Portugal and Austria remain highly vulnerable across the sample period. Market resilience starts to pick up slowly in the post-GFC period. Figure 4.8 depicts an increase in resilience for the Austrian market that coincides with commencement of Greek's new austerity measures. Resilience starts to build in the periods that follow for Greece and Portugal up until the new austerity measure is adopted as the eurozone crisis slows down. Vulnerability amplifies for Greece and Portugal with new Greek austerity measures in place. We conjecture from DY that Greece is more at the receiving end of shocks from its peripheries than transmitting the shocks to others. **2**. Gyrations in the vulnerability of Croatia is more pronounced than for Ireland and Belgium. While the amplification in vulnerability levels off for Ireland and Belgium, as the eurozone crisis becomes full-fledged, the Croatian pattern remains volatile. Facing the dampening of exports, vulnerability for Belgium and Croatia amplifies. .	**1**. Preceded by a strong amplification in vulnerability facing the eurozone crisis, the Austrian market's vulnerability begins to drop with Greece adopting new austerity measures. The Austrian pattern resonates well with DY, and also holds for Portugal. Moreover, MHD captures that in the most recent periods, with the eurozone crisis subsiding, Greek resilience building accelerates, while vulnerability dominates the risk curve of Portugal. **2**. MHD provides better information concerning Croatian swings in the systemic risks compared to DY. In contrast with the information produced with DY, MHD supports that Croatian systemic risk swings lie well within the boundary outside the vulnerability region. Croatian market remains rather resilient to shocks across the sample periods. As opposed to the DY pattern, the Belgium systemic risk pattern depicts rapid deceleration in vulnerability, moving the curve towards neutrality in the post-GFC period, and also holds for Ireland. Albeit smaller spikes in vulnerability are discernible for Belgium and Ireland during the eurozone crisis compared to the spikes observable during the GFC, the markets are becoming more resilient.	**1**. Contemporaneous small surges in volatility due to shocks inherent to local factors have little effect on the GC markets, except for very recently. This suggests contagion influences the GC markets since the onset of the eurozone crisis. During the eurozone crisis and with the phases of Greek austerity measures, Figure 4.18 shows that positive in-shocks from return spillovers for Portugal, Ireland, Croatia, Austria, Belgium and, especially, Greece far exceeds any localised volatility risk. **2**. In the period following the eurozone crisis, Portugal, Greece and Ireland become more susceptible to volatility interconnections than to contagion. This indicates that these markets have less risks due to contemporaneous associations with peripheries. This does not hold for the vulnerability patterns of Belgium and Croatia, and Croatia also remains strongly correlated to the peripheries.

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Table 4.3: Empirical Analysis comparing DY, MHD, SVD

	Vulnerability		
Blocks	DY	MHD	MHD-SVD
OED	As the USA market recovers from debacles following the dotcom bubble and the Japanese market rebounds from the long-lasting debt crisis, resilience in both the markets peaks profoundly. These two major economies recover results with similar outcomes for other deeply connected markets such as Germany, South Korea and Singapore. Canada, New Zealand and Norway's vulnerabilities slowly grow since the GFC unfolds. The Canadian curve shows several episodes of short-term resilience building along the way. However, Canada and New Zealand's vulnerability curve shifts up with the inclusion of oil and commodity indices, but less so for Norway. The strongest resilience build-up for Russia is depicted during the USA embargo on Russia. It emerges that with the embargo, the limited node connections cast out risks for Russia.	Consistent with DY, the MHD plots for the USA and Japan show the strengthening of resilience in early 2000. While vulnerability for the USA and Canada remains positive all along, Japanese resilience peaks correspond to the phases of confidence building in the markets and preceded by recovery periods associated with all major global events. This holds to a much less extent for Norway, and to a moderate extent for New Zealand. From MHD, what re-emerges is that these three countries' markets suffer from the same market assessment of default risk. Unlike what DY depicts, the Russian market remains resilient for the sample period with MHD.	Strong local volatility factors casting off risks are attributable to the USA, Canada, Russia and Norway in the eurozone crisis. This is not so for Japan, which highlights Japanese vulnerability to conditional correlations with the other peripheral markets as depicted in Figure 4.19. We find that in the post-eurozone crisis and with the onset of export drag, Russia, Norway and Japan become highly susceptible to contagion followed by some degree of decoupling.

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Table 4.3: Empirical Analysis comparing DY, MHD, SVD

	Vulnerability		
Blocks	DY	MHD	MHD-SVD
OEE	In line with the global literature, Figure 4.10 depicts the heightening of resilience for large exporters of oil such as Saudi Arabia, Iraq and Nigeria. This is explained global investors' move towards energy securities and away from MBS in the advent of GFC. The increasing resilience for Kuwait and Israel is better explained by boosted investors' confidence as the Iraq invasion is happening. This is due to the conflict between Iraq and Kuwait and Israel in the regime. However, Venezuelan resilience building in the most recent periods can only be attributed to its disentangling of connections, as the whole economy is at a worsening spiral. The vulnerabilities for Israel and Nigeria significantly increase when adding oil and commodity shocks to the system.	MHD perfectly captures the resilience building for Saudi Arabia in DY. However, what DY fails to capture is the strong jump in vulnerability that follows. MHD further captures the neutralising of systemic risks emitting from Iraq. This finding can be better conceived as providing a better rationalisation for the cessation of Iraqi market activities with the invasion. Hence, DY is more misleading for the Iraq case. Despite Kuwait and Israel's resilience building given by both DY and MHD, MHD identifies that this is not as strong for both the markets in comparison to what is drawn from DY. In contrast, DY does not emphasise the peaks in Israeli vulnerability with the GFC. With the fall of Iraq, weakening of OPEC and increasing USA support for Israel in the regime, it is conceivable that Western investors' interest in the Israeli market spikes as barriers drop. This explains the spike in vulnerability for Israel during the GFC with the deepening of interconnections with the USA. Conspicuously in the MHD of Venezuela, which is unlike the results of DY, the economic collapse of Venezuela only fuels its vulnerability in the most recent periods. Nigeria remains vulnerable across the sample period with DY and holds for MHD.	We replace the Middle Eastern markets with New Zealand and Mexico as major oil exporting countries. We find the vulnerabilities in both these markets are coming more from contagion and less from local volatility factors.

Table 4.4: Empirical analysis comparing DY, MHD, SVD

Transmission			
Blocks	DY	MHD	MHD-SVD
AC	**1**. Transmission mounts for India, Singapore and Thailand during the GFC. **2**. South Korean transmissions amplify during 2002–2004 when the global economy was riddled with many crises. **3**. The Malaysian and Philippines markets demonstrate neutral to dampening transmissions overall. **4**. Inclusion of oil and commodity indices amplifies transmission during crisis, but only for India and South Korea. **5**. Little amplification in transmission is observed for all participants facing the GFC.	**1**. Patterns accord well with DY results for India, Singapore and Thailand during the 2006–2008 GFC period. **2**. As opposed to DY depiction, the South Korean transmission bears a negative sign, suggesting the dampening of transmission is dominant during 2002–2004. **3**. The Philippines and South Korea portray negative transmissions, the only exception of which was during the GFC event. This supports the DY argument. **4**. Positive transmissions are plotted for all markets during the GFC, similar to the DY observations.	Transmissions in the AC cluster shows India, Malaysia and the Philippines are becoming more epidemic in nature. Strong volatility amplifications in Thailand and Singapore suggest transmissions of crisis from these markets are more endemic in nature.

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Table 4.4: Empirical analysis comparing DY, MHD, SVD

	Transmission		
Blocks	DY	MHD	MHD-SVD
EC	**1**. We find a resurgence in transmission for Germany during 2002–2004 similar to that of South Korea mentioned earlier. **2**. France and UK transmissions amplify in the advent of the eurozone crisis, while remaining neutral in earlier crises. **3**. Australian transmissions slightly amplify during the GFC and export crisis. Dampening prevails in the transitions between crises. **4**. Chinese transmissions amplify mostly with the recent Chinese crisis. Earlier, Chinese transmissions amplify only during the GFC.	**1**. With Germany we again find negative transmissions across 2002–2004, rejecting DY depiction. This is similar to South Korean transmissions mentioned in the earlier cluster. **2**. Consistent with DY, MHD shows positive transmission across the eurozone crisis preceded by a negative dampening during the GFC for both France and the UK. **3**. MHD is consistent with DY for Australia. **4**. The findings are similar to DY.	**1**. Most in this cluster turn more epidemic, especially following the onset of Eurozone crisis. In contrast, short-lived volatility rises profoundly for China and Australia, corresponding to the Chinese crash. **2**. Importantly, the patterns in Figure 4.22 outline that the transmissions from this cluster are, on average, epidemic in the cooling-off period from the eurozone crisis. Soon after, markets revert to being endemic to varying degrees.

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Table 4.4: Empirical analysis comparing DY, MHD, SVD

Transmission			
Blocks	DY	MHD	MHD-SVD
GC	**1**. Transmissions amplify for Greece, Portugal and Ireland with the eurozone and Greek crises. Recently, Ireland transmissions ascend following a descend. **2**. Belgium shows escalating transmissions facing the recent export shrinkage.	**1**. Greek transmission shows small surges in the positive direction, followed by strong negative dampening, mostly during the eurozone. In contradiction to DY, the strongest surges for Portugal and Ireland are found during the GFC. **2**. Belgium transmissions remain neutral to dampening. Unlike DY, the positive and negative estimates offset strong amplifications for Belgium. **3**. As the Greek crisis unfolds, positive transmissions resurge for Croatia. This is not identified with DY.	**1**. Risk transmissions from this cluster appear not highly epidemic. Strong volatility sways simultaneously over Ireland and Greece following on from when the first Greek austerity measures are adopted. **2**. Figure 4.23 highlights that in the most recent periods, Belgium and Austria cast off some risks at an epidemic level.

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Table 4.4: Empirical analysis comparing DY, MHD, SVD

Transmission			
Blocks	DY	MHD	MHD-SVD
OED	**1**. We find the strongest transmissions for the USA and Japan during the dotcom bubble. Transmissions resurge during the GFC and GC for the USA. Japanese transmissions decelerate during this period only to amplify in the post-GC period, possibly corresponding to global export shrinkage coupled with oil flat. Crucially, transmissions are reduced with the inclusion of oil and commodity indices. **2**. Russian transmissions amplify in all major events across the sampling periods, leading to a phenomenal jump facing the recent Russian financial crisis of 2014–2015. Inclusion of oil and commodity indices slightly dampen the transmissions. **3**. The transmissions for both Canada and Norway sharply descend, corresponding to a dramatic decline in global oil prices immediately after climbing to an apex in the post-GFC period. For both these markets, oil and commodity inclusion reduces transmission levels. **4**. Gyrations in the transmissions of New Zealand do not show sharp oscillations.	**1**. The anticipated 'conduit effect' of the USA and Japan (BIS, 1998), which drives transmissions up from the USA, Japan to other countries and is supported in earlier studies, is dismissed with MHD. We identify dampening for the USA market during the dotcom bubble. Conversely, dampening in transmissions from the Japanese markets is preceded by a strong amplification during the dotcom bubble, suggesting the 'conduit effect' may still hold for Japan. The dampening for Japan is attributable to the debt crisis predominating during that period. **2**. Risk transmission from Russia remains strongly positive for the most part, with exceptions only during the advent of the GFC and Russian crisis of 2014–2015. **3**. The patterns accord well with the DY findings for both Canada and Norway. Additionally, the Norwegian market shows neither a dramatic dampening nor sharp amplification in its transmissions across the sample period, and the DY estimates may have misrepresented the degree of transmissions for Norway. **4**. The transmissions that New Zealand emit are predominantly near its mean. Except for a few spikes following the GFC and GC, New Zealand transmissions remain neutral to other major crises or volatility shocks.	**1**. Risk transmission stemming from locally induced volatility can be attributable to the USA, Russia, Mexico and Norway, especially following the recent Russian economic crisis and oil supply shock. In contrast, Japan, New Zealand and Canada are passing risks on to others in the network, without inflicting locally induced volatility in the process. Hence, we can refer more to these markets as 'conduits' than to others in recent years. **2**. In the post-Chinese crisis, Japanese and New Zealand transmissions might become more pandemic than endemic.

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Table 4.4: Empirical analysis comparing DY, MHD, SVD

Transmission			
Blocks	DY	MHD	MHD-SVD
OEE	**1**. Transmissions peak during the GFC and export shrinkage for the Saudi Arabian market. Oil inclusion causes an overall drop in the transmission curve for this market. **2**. We identify transmissions amplifying with the onset of Iraq invasion for Israel. Transmissions from this market resurge again as the Greek debt crisis rolls into a full-fledged eurozone crisis. **3**. While Iraq's invasion of Kuwait does not decelerate the transmissions emitting from Iraq, this leads to the complete nullification of transmissions from Kuwait. A substantial amplification of transmission from Iraq in the ensuing GFC is identified with DY. **4**. Among the non-Middle Eastern OEE countries' markets, the Nigerian market shows sufficiently proximate contemporaneous small surges in transmission across the years spanned by our samples, and Venezuelan transmissions soar facing the export shrinkage.	**1**. Despite positive transmissions during the GFC complementing the findings of DY for Saudi Arabia, the transmissions are predominantly negative except for the GFC. **2**. Neutral to positive Israeli transmissions span the entire sample period, with small surges in the ensuing export shrinkage and stronger surges during Iraq invasion. **3**. DY fails to capture the strong amplifications in the Kuwait market with the Iraq invasion and export shrinkage. This suggests the Kuwait market is on the rebound as the Iraqi dominance subdues, becoming a central oil exporting partner in the periods that follow. **4**. DY patterns do not accord well with MHD for Nigeria, and is not conducive to explaining fundamentals driving Nigerian market risk. DY fails to capture the dampening of Nigerian markets during the oil crisis following the Iraq invasion and also transmissions surging with the USA bubble. However, DY and MHD both identify the build-up of Venezuelan hyperinflation in the most recent period, as both show the unprecedented rise in transmissions from Venezuela.	

Chapter 5

Calm before the storm: an early warning approach

5.1 Introduction

The many facets of global financial crises have heightened research interests in systemic risk and contagion. Naturally, investors expect higher returns for holding risky assets. Indeed, investors' utility function readily changes in response to an increase in the degree of total risks in a market as a crisis unveils. In this chapter, we investigate inter-temporal changes in investors' risk tolerance responding to the degree of systemic risk by propose dynamic information maps visualising shifts in investors' risk tolerance.

In this chapter, we measure the changing nature of investors' risk preference corresponding to cycles of systemic risk in the market. Further, we propose a means of visualising dynamic information transmission maps using self-clustering of nonlinear inputs of investors' risk preferences across time to the extent that it leads to crisis generation. The expectation maximisation/artificial neural network based self-clustering maps highlight information transmission pathways in a pool of markets in response to random stimuli stemming from speculation or fear of crisis. The maps are analogous to slices of brain scans lit up by firing neural pathways and, as such, are easily processed visually. We show that the dynamic maps can be considered an extension of widely acceptable risk estimates, and are easily conceivable by general practitioners in the risk management spectrum.

We address four key questions regarding investors' time-varying risk preference in response to vulnerability index for a market. First, we investigate the direction of investors' risk preference with changing degrees in the vulnerability index. Second, we compute the significance of investors' risk preferences over time. Third, we present a crisis transmission pathway over two decades, highlighting the least-resilient pathway in the system. Finally, we examine whether the vulnerability-related public information transmission pathway gauged from investors' risk preference across time may contain some predictive power concerning the crisis transmission pathway and some early warning potential.

An important concern arising from the listed questions may be, why these questions are important or how they connect to a key logical argument that enhances our state of knowledge.

Our objective in this chapter is to implement a method that will aid in understanding the role of frictional networks in dampening resilience of any given market in a system of markets. In addition, we address that investors parse crisis-related information differently, which changes the corresponding risk tolerance, which generates further vulnerability in the market. Our objective is to propose means allowing managers of systemic risk control over information spread in times of crisis, and to simulate the effects of an

alternative intervention in the information pathway to detect best possible actions to restrain unprecedented risk speculation exacerbating in any market. This, in turn, increases control over systemic risk for a recipient market in the system.
The studies applying self-organising maps (SOMs) as a deep unsupervised learning process to investigate systemic risks is uncommon and fairly new. For example, Resta (2016) presented stock market clusters with SOMs. While Marghescu et al. (2010); Barthélemy (2011); Sarlin and Peltonen (2013) and Betz et al. (2014) somewhat popularised the use of SOMs in the field of finance, early papers had applied other artificial neural network methods attempting to make crisis predictions in a system of financial institutions or markets (Liu and Lindholm, 2006; Apolloni et al., 2009). However, Betz et al. (2014) argued that SOMs have better prediction properties than traditional latent models, and contribute as an early learning system in crises prediction. For studies using SOMs in the field of financial crisis and risk management, see Liu and Lindholm (2006); Peltonen (2006); Apolloni et al. (2009); Marghescu et al. (2010) and Betz et al. (2014), for network mapping see Barthélemy (2011) and Sarlin and Peltonen (2013) and for market clustering see Resta (2016).
We aim to propose an early warning system for vulnerability transmission that corresponds with a pattern of risk tolerance resulting from pre-existing vulnerability and, thus, forming a loop. Notably, forward–backward, propagation-based, updating algorithmic approaches became more reliable than other methods, such as quasi-newton algorithms, with the sequential processing of random sub-patterns resulting in indices of global minima and proposing a more efficient vector quantisation. Hence, the compression of high-dimensional data to a lower-dimensional topography weight that is generated with sequential clustering leading to the identification of the least distant target vectors; and passing an early stop criteria that controls the over-identification parameter, presents converging patterns despite random initialisation. To our knowledge, this work is the first attempt to investigate an information transmission pathway stemming from vulnerability dynamics with similar maps, indicating the potential of crisis accumulation. In this chapter, we use risk tolerance, risk preference, risk sensitivity and aggregate risk behaviour interchangeably, referring to degree of amplification and dampening in the risk aversion index gauged from our proposed framework.
Our dataset encapsulates daily returns of the aforementioned markets from 1998 to 2017. Our sample period encompasses 10 episodes of global crisis events of various degrees. We use a balanced sample of 30 international equity markets: Australia, Austria, Belgium, Canada, Chile, China, Croatia, Ecuador, France, Germany, Greece, India, Iraq, Ireland, Israel, Japan, Kuwait, Malaysia, New Zealand, Nigeria, Norway, Portugal, Russia, Saudi Arabia, Singapore, South Korea, Sri Lanka, Thailand, the Philippines, the USA, the UK and Venezuela. We further classify our markets into groups based on similitude in macroeconomic fundamentals (or similar traits): export crisis, including markets from leading export (oil and non-oil) countries, oil exporting emerging countries and oil exporting developed countries; Greek debt crisis-affected European countries' markets; and 1997 Asian crisis-affected Asian markets. According to BIS (1998) and Baur and Schulze (2005) the USA and Japan acted as conduits during many of the past events. For details on the data used and the span of crises in our sample, see Tables 3.1 and 3.2 presented in chapter 3.
In what follows, we present the empirical framework is presented in Section 5.1, before the data is explained in Section 5.2. We present the results in Section 5.3 before concluding the chapter in Section 5.4.

5.2 Empirical framework

In this chapter, we estimate risk tolerance parameters using a univariate GARCH in mean model for each of the returns indices in the sample to understand the degree to which the transmission is received by the index in the interconnected matrix. In other words, we are examining if the swings in vulnerability during a crisis period are led by investors' risk preference at any given time. In what follows, we estimate DY spillover indices and model risk in daily returns with respect to estimated vulnerability indices.

To begin with, we need to estimate the vulnerability indices from DY spillover indices. The Diebold and Yilmaz (2012) proposed n-step ahead forecast error variance decomposition matrix in a VAR framework categorises unsigned connectedness between N covariance stationary variables with orthogonal shocks.

We have discussed the empirical method of Diebold and Yilmaz (2012) in chapter 3.

Now, execution of the conditional algorithm leaves us with the vulnerability index produced with rolling DY conditional variances that we use as input for the next block of empirical analysis. We estimate the dynamics between return and risk with a bivariate GARCH-M model presented here. We begin by estimating the expected return of indices regarding its risk when exogenous shock from return spillover received from others $r_{spilloverfrom,t}$ is added to the following model.

$$\mu_{i,t} = \gamma_0 + \gamma_1 r_{spilloverfrom,t} + \varphi\sigma_{i,t}^{\rho} \tag{5.1}$$

Later we re-analyse the model with $r_{oil,t}$ to examine the effect of return shocks corresponding to the oil index with

$$\mu_{i,t} = \gamma_0 + \gamma_1 r_{oil,t} + \varphi\sigma_{i,t}^{\rho} \tag{5.2}$$

The uni-variate GARCH in mean model is

$$\sigma_{i,t}^2 = \alpha_0 + \alpha_1 \upsilon_{i,t-1}^2 + \beta_1\sigma_{i,t-1}^2 \tag{5.3}$$

where $\upsilon_{i,t} = r_{i,t} - \mu_{i,t}$. The parameters to estimate here are $\theta = \{\gamma_0, \varphi, \rho, \alpha_0, \alpha_i\beta_i\}$. Here $\rho > 0$, the estimated parameter φ gives us Risk Averse : $\varphi > 0$, Risk Neutral : $\varphi = 0$ and Risk Taker : $\varphi < 0$ indicators. In addition to helping with estimating the parameters by maximising the negative log-likelihood function, it also allows us to derive the global minima with

$$\ln l_t(\theta) = -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln\sigma_t^2 - \frac{1}{2}\ln z^2, \tag{5.4}$$

the standardised residual $z_{i,t} = \dfrac{\upsilon_{i,t}}{\sigma_{i,t}}$ helps to implement diagnostic test on the model. We perform test of risk-neutrality using the Wald test by testing the restriction $\varphi = 0$. Here, the null hypothesis is $H_0 : \widehat{\varphi}_{i,t} = 0$ against the alternative hypothesis $H_1 : \widehat{\varphi}_{i,t} > 0$. We perform our analysis N times for each vector, generating risk aversion indices alongside the significant test results in vectors. With forward propagation we derive an index of local minima for each market corresponding to its underlying vulnerability. Next, we take the empirical data from the signed spillover index that we generated in chapter 4 [1] and compare with signed risk aversion indices that we produce in the next section.

Dungey et al. (2017a) proposed the signed spillover index, which overcomes the limitations of DY spillover estimations proposed by Diebold and Yilmaz (2012) as systemic risk estimates. These signed spillovers discern both the magnification and dampening effects of contemporaneous shocks compared to unsigned estimations in the markets. MHD measures the signed weights of shocks by simply estimating impulse responses weighted by

[1] See page 111 for empirical framework of the signed spillover index

residuals. We extract the TO and FROM signed spillovers from row and column elements of MHD $N \times N$ matrix estimate. The complete empirical framework of MHD is outlined in Chapter 3. In what follows, we generate SOMs that compute neural networks from risk aversion indices.

5.2.1 Dynamic-mapping

We examine the effect of information propagation in exacerbating a crisis for a market facing a high degree of systemic risk with multiple levels of risk sensitivity with Self organizing information maps (henceforth $SOM^{information}$). The changing position of nodes during N recursive estimation in the k-dimensional space illustrates the direction of information propagation that may lead to a heightening of systemic risks in the period following immediately after.

$SOM^{information}$ is a class of deep unsupervised clustering that meets expected minimisation criteria across weights. Presented with input nodes (in this case risk aversion indices with systemic risk as a covariate) across two-dimensional Euclidean space, the classic backward–forward propagation, in linear combination with nonlinear functions, project estimated weights drawn from least distances with expected cluster centres onto a compressed space of squared dimension. This process is initialised with multinominal probabilistic distribution. In summary, the recursive process outlined in the computations group the input arrays into intermediate arrays, reducing the dimension of inputs. Convergence results in lower-dimensional classifiers/outputs. Overall, the SOM method clusters nonlinear inputs better than does K-means clustering clustering (Clark et al., 2014; Kohonen, 1998)[2] .

The steps in the process initiates with the principal component surface populating a lattice with an array of random /stochastic gradient weights[3]. Next, the recursive optimisation converges to local minima scanning across all data points and, in doing so, updates centres on the lattice. The convergence is reached when least distant outputs from input nodes by changing of their weights is achieved and is denoted the 'best matching units' (BMU) (the analytic gradients of the weights construct the popularised hidden layers of edges). In other words, the nearest neighbours are assigned higher weights in a neighbourhood space, resulting in the centres forming a sphere around the lattice. In the process, BMUs are computed in a two-dimensional space by minimising Euclidean norm, gradually forming a sphere of nodes, in which the distance between i and j nodes are $\varepsilon = \sqrt{\sum_{j,i=0}^{n} (v_i - \omega_j)^2}$. Finally, a map is retrieved by presenting the sphere in a two-dimensional grid of neurons to which the non-linear structure in input data is optimally fitted.

Crucially, the 'sequential processing' of the algorithm ensures that each weight is updated to its corresponding input nodes and propagated backwards in the base using the updating function,

$$w_{t+1} = \omega_t + \theta_t \sigma_t \varepsilon_t \tag{5.5}$$

The updates are scaled with the learning rate and influence rate σ_t for curve fitting.

[2]K-means clustering remains better in clustering linear inputs.

[3]The weights are assigned onto each data point in the input vector. The process involving activation of objective function is a multi-class generalisation process. Optimising the objective function, known as network training, is analogous to polynomial curve fitting as the target vector is Gaussian. The algorithm is targeted to minimise the loss function (target-prediction) by updating gradients of node weights in a sequential process of backward-forward propagation.

Finally, the influence rate [4] depicts the influence of each weight on the classifiers:

$$\theta_t = e^{\left(-\dfrac{\varepsilon^2}{2\sigma_t^2}\right)}$$

The influence rate assigns non-zero units for BMUs and decreases if the distance between the nodes in BMUs increase. This is analogous to multinomial probabilistic classification.

We generate an information map following the methods suggested by Sarlin and Peltonen (2013). Upon nonlinear convergence, the maps resemble sparsity, no event illuminate with lighter colours. Failure to do so presents a high degree of nonlinear cycles, represented by the darker regions. The picture that emerges shows an event is transpiring in the information transmission pathway compared to no events occurring. Technically, this map is known as 'iris flower map' clustering, which is observed as high degree of nonlinearity with darker colours compared to converging clusters with lighter colours. Here, (x, y) locations represent the positions of the markets' nodes in the two-dimensional representation.

5.3 Data

We draw on daily dollar denominated stock price indices for 30 equity markets from Asia–Pacific, Europe, the Americas and the Middle East for the period 1 January, 1998 until 15 September, 2017. Our data are sourced from Thompson Reuters Datastream. We account for 10 major crisis events in our sample period. The descriptive statistics on the filtered data is presented in Table 4.1. We do not find significant correlation in the residuals, ruling out inconsistency and rejecting multicollinearity in our sample data.

We estimate returns using first difference of natural logarithms. As suggested by Forbes and Rigobon (2002) and Hyndman and Athanasopoulos (2014) we scale down the time zone difference by filtering our data with two day moving averages. In principal, moving averages filtering reduces white noise optimally by focusing out the sharpest edge points. This guideline underpins the relevant network and risk literature (Joseph et al., 2017; Zhong and Enke, 2017; Elliott and Timmermann, 2016; Chen et al., 2016; Ferreira and Santa-Clara, 2011; Vaisla and Bhatt, 2010; Atsalakis and Valavanis, 2009; Cont, 2001; Granger, 1992; Balvers et al., 1990; Fama, 1976).

The importance of using equity returns in empirical studies for distinguishing the properties between indicators has been discussed in detail in the relevant literature. While Cont (2001) focused on non-linearity and persistence, Granger (1992) pointed out the non-stationary properties of equity returns data. In the past, Fama (1976) provided evidence of daily returns being more non-Gaussian compared to intra-day returns. Recently, asset returns have been reported by Joseph et al. (2017) to have non-Gaussian, time-varying, persistent characteristics with smooth compact support over low-frequency spectral content. In contrast Zhong and Enke (2017); Wollschlager and Schäfer (2016); Joseph et al. (2011); Atsalakis and Valavanis (2009); Joseph and Larrain (2008) contended that daily returns are highly non-linear, volatile and negatively skewed. Despite the scientific discourse, the benefits of using asset returns with appropriate pre-processing outweighs its harms in financial economics.

Additionally, filtering with MA is well supported in the literature. As Joseph et al. (2017) suggested that MA filtering increases the quality for both continuous or discrete time series in both time and frequency domains. Smith (1997) also provides evidence of MA handling discrete time series with greater accuracy but in a less complicated manner.

Research into systemic risk and predictive modelling widely uses asset return indicators, and applies both non-parametric self-learning techniques and parametric statistical

[4]This rate substitutes the popularised score function in generalised neural network architecture.

methods (Joseph et al., 2017; Zhong and Enke, 2017; Joseph et al., 2016; Elliott and Timmermann, 2016; Chen et al., 2016; Ferreira and Santa-Clara, 2011; Vaisla and Bhatt, 2010; Atsalakis and Valavanis, 2009; Cont, 2001; Granger, 1992; Balvers et al., 1990). We complement Joseph et al. (2017, 2016); Atsalakis and Valavanis (2009) and Zhong and Enke (2017) by pre-processing our data with an appropriate window choice with the aim to avoid aberrations caused by discontinuations in returns data. We complement Oppenheim and Schafer (2014) and Forbes and Rigobon (2002) who reported the best results with window size 2; this also underpins the 'spectral windowing' theory. In what follows, we will discuss estimation outputs and results, followed by policy implications and remarks.

5.4 Empirical results

Central to scientific discourse lies in which macro-economic factors determine the dynamic co-movement of global markets in times of crisis. This discussion leads to the argument that volatility amplification in the market during crisis indicates a dilemma on the proportion of contagion identifying crisis propagation relative to other macro-economic factors (Kocaarslan et al., 2017). Studies have attempted to explain financial contagion, and investor sentiment has made its way into recent research (Corsetti et al., 2005; Boyer et al., 2006; Chiang et al., 2007; Syllignakis and Kouretas, 2011; Celık, 2012). Kodres and Pritsker (2002) pointed out that information asymmetry is minimal in calm periods and leads to reduced hedging activities. In contrast, investors expect positive jumps in information linkage dynamics during crisis periods. Further, the selective shifting of funds across global markets and alternative investment areas, such as oil, eventually heightens systemic risks for any given market. Recently, Kocaarslan et al. (2017) stated that important macro-economic factors may only affect crisis propagation in global markets through investors' expectations of information linkage and reactions to information dynamics.

In this section, we support this school of studies by producing analytical results presenting the dynamics of investors' risk perception corresponding to signed spillover indices across crisis and calm periods. We also produce dynamic information maps explaining information linkages during such times. These findings, combined with systemic risk analysis, provide a holistic view on how crisis generates and propagates across markets.

Regarding the window size for dynamic analysis, it is crucial to discern cyclicality in the signals without sacrificing important information (Kapadia et al., 2012; Romer and Romer, 2015). After much deliberation, we decide on 200-day window for both risk perception and signed spillover indices. We gauge DY spillovers with H = 10 step ahead forecast error variance decomposition into dynamic risk perception estimates as covariates.

We classify our markets into Asian crisis (AC), Greek crisis (GC), export crisis (EC) markets, oil exporting developed (OED) and oil exporting emerging (OEE). We present the signed risk aversion indices juxtaposed against signed spillovers (TO and FROM), respectively, in Figure 5.1, Figure 5.2, Figure 5.3, Figure 5.4 and Figure 5.5. In doing so, we examine the dynamics in investors' risk tolerance corresponding to the degree of transmission and vulnerability in any given period. Hence, we understand how readily available information corresponding to dynamics of postulated crisis changes investors' risk tolerance. Further, the order of the clusters is maintained in the axes of dynamic maps capturing the information transmissions.

We clearly demonstrate the changing interconnectedness affecting investors' risk tolerance in Figure 5.1, Figure 5.2, Figure 5.3, Figure 5.4 and Figure 5.5. Henceforth, we use risk tolerance, risk preference, risk sensitivity and aggregate risk behaviour interchangeably for the remainder of the paper. Periods of crisis can be distinguished by the widening gaps between transmission and vulnerability. A discerning feature in the figures is the higher gaps that are exerted on dynamic risk tolerance during crisis periods, indicating that investors' risk preference readily changes with the degree to which a crisis is interconnected. In general, high-level risk-taking is derived from the figures during turmoil periods, which is with Dungey et al.'s (2010a) notion of hypersensitivity. The heightening in risk-taking may indicate the contribution of investors' heightened reaction during a crisis period, which contributes to exacerbating the crisis transmission and accompanying amplifications in vulnerability. This finding is in line with the suggestions outlined by (Chudik and Fratzscher, 2011; Mondria and Quintana-Domeque, 2013; Dungey and Gajurel, 2015).

5.4.1 Asian crisis markets

In this section, we examine the signed spillovers against the risk neutrality index presented in Figure 5.1 to discover whether investors' aggressiveness affects the degree of systemic risk in the AC markets cluster. In this cluster, we include India, the Philippines, Malaysia, Thailand, Singapore and South Korea. These countries' markets are selected to investigate the systemic risk dynamics corresponding to multiple events of crisis since the Asian financial crisis. We further postulate crisis originating from investors' risk preference, driven by accessible crisis-related information.

First, for India and the Philippines, we find both markets lying dormant in terms of investors' aggressiveness, except for the periods leading from the1997 Asian financial crisis. Both markets remain vulnerable to other markets while the corresponding risk aversion remain dominant. Further, we find that while vulnerability plunges for India in the periods following the GFC, the transmissions pick up. However, the Indian investors remain mostly risk averse. It is only after the European crisis that Indian investors' risk tolerance amplifies. We discern similar patterns all the more for the Philippines. However, in Figure 5.6 we find the p value from the Wald test remains in the region of not rejecting the null of risk neutrality in the Asian financial crisis, but starts to shift towards the region against the null of risk neutrality. We find this holds more so for the Philippines in the post-GFC period. Both markets cement the notion that markets may remain vulnerable even with low–risk-tolerant investors. Additionally, higher risk tolerance may further fuel risk transmissions to other markets.

Next, from the signed spillover indices we find that vulnerability predominates for Malaysia and Thailand across the sample period. The only exception is a strong upswing in transmission from Thailand in the post-European crisis period. The investors in both markets largely demonstrate strong risk neutrality. The curves show a pull towards risk-taking during and after the GFC. This corresponds to a Wald significance test lying around the risk neutrality region, with the significance curve moving away from risk neutrality only after the GFC.

Then, we identify strong contrast in the risk tolerance for Singapore and South Korea. Despite similitude in the transmission and vulnerability derived from signed spillover indices for both markets, investors in Singapore are highly aggressive compared to investors from South Korea, who are mostly risk averse in the post-GFC period. This leads to higher vulnerability for Singapore compared to South Korea. Moreover, a more significant shift from the null of risk neutrality with accompanying jumps from these two markets show investors become either more risk averse or more risk aggressive.

In all cases examined in Figure 5.1, we find that Asian investors transition from risk neutral to risk-taking with the heightening of accompanying vulnerability, especially after the GFC.

5.4.2 Export crisis markets

In this section, we discuss the cluster representing countries affected by plunging total exports since 2016. We include Germany, France, Australia, China, Chile and the UK. We investigate the signed systemic risk indicators while also presenting in Figure 5.2 investors' risk positions in these markets, which we believe are responsible for higher systemic risks.

First, we find both vulnerability and transmissions for Germany and France are mutually exclusive. The degree of transmission for Germany remains higher than for France, especially during the GFC. Conversely, France remains resilient in the post-European debt crisis, which contrasts with German patterns. Although, Figure 5.2 depicts a higher risk tolerance for France than for Germany, Figure 5.6 shows a diminishing significance for risk tolerance in Germany, and investors in both markets are predominantly neutral across the sample.

Next, the Australian transmission is energetic across important crisis periods, especially during the GFC and, more recently, at the onset of Chinese crisis. The accompanying vulnerability levels indicate that with jumps in risk transmissions, Australia becomes more susceptible to in-shocks. While the corresponding investor sensitivity seems to lean towards high-risk preferences among investors, risk significance indicates that investors respond with higher aggregate risk tolerance. This corresponds to jumps in risks, and even more so in the post-GFC period. Overall, Australian investors prefer to remain risk neutral in calm periods.

Moving on, we find China becomes more resilient, especially during the recent Chinese crisis. We identify the strengthening of such resilience when compared to a similar combination of transmission and vulnerability during the GFC. Investors' aggregate risk tolerance decreases in the risk preference index, with the corresponding significance index depicting a shift towards the direction of risk aversion, while risk neutrality remains highly significant.

Turning to the remainder of the markets in this cluster, Chile and the UK both remain resilient to negative in-shocks. However, this is dictated by stronger transmissions from the UK, as the UK market nodes are located near high-risk markets, referred elsewhere. Risk preference in the Chilean market turns towards the extreme, although a significance test does not hold. For Chile, significant risk-taking is evident during tumultuous times only. In contrast, risk-taking as an aggregate behaviour dominates over the British market in the risk preference index, which is in line with the gauged significance, especially since the onset of the GFC.

In all the markets discussed in Figure 5.2, the patterns accord well with the fact that risk-taking increases corresponding to amplifications in systemic risk propagation during periods of turmoil, with investors remaining neutral in other times. In other words, investors' access to crisis-related information fuels herding or risk tolerance further in the market. This, in turn, propagates stronger shocks to other markets by building up systemic risks, consequently serving as a propagation channel for future crises.

5.4.3 Greek crisis markets

In Figure 5.3, we demonstrate the spillovers from countries that were primarily affected by the European crisis, coupled with risk neutrality estimates. The countries are Greece, Portugal, Ireland, Belgium, Croatia and Austria. Jumps in the risk tolerance curve correspond well with signed spillover indices, signifying its importance in driving the dynamics in the degrees of systemic over time.

The risk preference index for Croatia, Austria and Ireland depicts opposing directional changes in the pre- and post-GFC periods. As the GFC unfolds, the Croatian risk preference index shows amplification in risk tolerance. In contrast, Austria and Ireland markets respond with a dampening risk tolerance. The significance curves support the patterns presented here by showing the curves moving away from the null of risk neutrality for Croatia and moving towards risk neutrality for Austria and Ireland. The corresponding gaps in the spillovers with the risk preference curves widen. This explains that higher risk-taking prior to a crisis fuels systemic risks further during a crisis despite investors' changing preferences when faced with a crisis. We conjecture that higher risk aversion during crisis results the markets falling further into a disaster. This is particularly true in the pre-GFC era; we identify a strong dampening of risk tolerance during each crisis period that is preceded by amplitudes in risk tolerance as shown in Figure 5.3. The corresponding systemic risk estimates demonstrate sharper swings in recent years, especially in transmissions from Croatia.

From Figure 5.3, initially we find a commonality in the risk sensitivity patterns of Portugal and Belgium because both the countries' investors are leaning naturally towards risk aversion from high-level risk-taking prior to the GFC. Nonetheless, the significance index presented in Figure 5.6 shows inconsistent risk aversion significance for Belgium, while depicting consistent significance for Portugal. This leads to build-up in resilience and corresponding gradual deceleration in transmission of risks from these markets, which affirms that an overall shift of investors' sentiment towards lower risk tolerance may lead to less propagation of shocks across markets.

Finally, examining the Greek curves, we find that investors in Greece are predominantly risk averse, especially since the USA subprime crisis sends the European markets into a downward spiral. We also show that despite Greece being a strong transmitter of shocks at the onset of European crisis, multiple austerity measures push the transmission down while simultaneously amplifying Greece's vulnerability to the rest of the world. In response, the high–risk-taking investors become risk neutral.

We suggest several points from this cluster. First, we show that a complete shift from risk aggressiveness to risk neutrality comes about due to a crisis, leading to resilience building for the concerned market. Second, we demonstrate that markets in this block are more vulnerable and investors are mostly risk averse. Third, we observe that repeated austerity measures suppress the transmission coming out from Greece, turning its investors risk neutral but at a cost of resilience to in-shocks. Next, we discuss oil exporting markets for both emerging and developing countries.

5.4.4 Oil exporting markets

Now, we discuss the countries that dominate the global oil markets. We cluster the countries in terms of economy sizes and characteristics. The OED cluster consists of the markets from the USA, Canada, Russia, Norway, Japan and New Zealand, and we discuss them in Figure 5.4. The OEE cluster comprises Saudi Arabia, Israel, Iraq, Sri Lanka, Nigeria and Venezuela, which we in Figure 5.5.

In Figure 5.4, we show that both Norway and New Zealand are both more resilient than others in this cluster. While Norway remains a big spreader, we find that since the GFC, New Zealand is becoming increasingly like a spreader. Consequently, New Zealand's vulnerability soars with the accompanying increase in risk tolerance among investors. In contrast, Norwegian investors show a diminishing pattern of risk tolerance. The significance index is consistent with the Norwegian pattern of risk preference, and is less consistent with the pattern emerging from New Zealand.

In terms of investors' risk tolerance, the Japanese and Canadian markets contrast sharply with the Russian market. In Figure 5.4, we show that both Japanese and Canadian investors are high–risk-takers for most part of the sample period. Moreover, the significance test on risk sensitivity for the Japanese market gives increasing support towards

Japanese investors becoming high–risk-takers since the GFC. However, this does not hold for the Canadian and Russian markets. Additionally, for both the Japanese and Canadian markets, the corresponding transmissions outweigh vulnerability. However, the Japanese swings are sharper in both directions compared to Canada, mostly during a global event. In contrast, the Russian investors are risk averse, and since the post-Russian crisis in 1998, the degree of transmission and vulnerability starts falling. Russian systemic risks did not amplify during the GFC; moreover, transmissions from Russia flatten out since 2008. In all cases, vulnerability remains low for these markets. Hence, we can conclude that with increasing risk tolerance, Japanese investors are contributing in the markets' ascending vulnerability since the global meltdown. Conversely, Russian and Canadian investors are less and play an important role in cooling down the risk propagation into their own markets.

Finally, we find a phenomenal amplification in the transmission swings from the USA during global meltdown, before it reverts back to normal level. Thereafter, we do not see such intensity in the vulnerability swings of the USA. Investors from the USA remain risk-takers with brief intermissions towards risk neutrality in post-turmoils across the sample period. Figure 5.6 suggests that USA investors are becoming more risk tolerant again as the economy recovers from the meltdown.

Turning to the OEE markets, we can suggest unequivocally that investors in all the markets are largely less risk tolerant, at least up until the emergence of the European crisis. We find the only exceptions are for Israel when the GFC erupts, and for Iraq in the post-GFC period. We also find a slowing down of transmission and vulnerability levels in recent years for all the Middle Eastern markets. However, Figure 5.5 shows that increases in vulnerability accompanies a heightening of risk tolerance for Nigeria since the European crisis. Conversely, the Venezuelan market drops flat with the economy spiralling down and, as such, only transmissions emit with liquidity flight. Risk neutrality for this market indicates little or no market activities, which may also hold for Iraq.

In all, we find that increases in vulnerability alone generally cannot be associated with lower risk tolerance, but may play an important role in subduing a transpiring crisis. However, transmission and vulnerability both amplify if investors in the markets facing a crisis are high–risk-takers. We conjecture that an increase in aggregate risk tolerance is caused more by friction, which increases risk-taking and causes an increase in systemic risk.

5.4.5 Crisis transmission maps

In this section, we present a visualisation of a least-resistant shock transmission pathway in the network of our markets, which can be considered an extension of vulnerability detection in network finance. This method proposes an easy visualisation of the complex structure of holistic associated network in our sample markets by producing maps similar to slices of brain scans lit up by firing neural pathways. We further compare the least resistant shock transmission pathway with the neural pathway lit up by changes in investor sentiments corresponding to information available to the investors at any point. By doing so, we provide evidence of an information transmission pathway preparing the way for crisis transmission across the adjacent pathways.

We contribute by producing visualisations of high-dimensional inputs by condensing matrices of both signed spillover gauges and signed risk neutrality measures into the meaningful self-organising clusters SOM^{crisis} and $SOM^{information}$, respectively. We begin by splicing the complete rectangular matrix into 40 successive windows, yielding a total of 80 maps capturing the dynamics in the association of crisis build-up and the underlying changes in information transmission. In Figures 5.7, 5.8, 5.9, 5.10 we present the dynamic crisis transmission maps produced with signed spillover matrices and in Figures 5.11, 5.12, 5.13, 5.14 we present the signed risk sensitivity indices gauged with multivariate GARCH optimisation. In the SOM dynamic representations, the horizontal and vertical scales give the individual markets and the markets in their respective clusters.

We propose to interpret the SOM^{crisis} by drawing on an analogy of a plateau: mid–dark colours represent fissures in the plateau, while the degree of vector quantisation are represented by light–dark-coloured neural pathways across the map. In addition to this interpretation, if shocks evincing a crisis are analogous to a flash storm in the system, then the rainwater naturally infiltrates through the fissures and sinkholes. Hence, the visible pathways represent the least-resistant pathway of crisis or crisis-related information transmission. In other words, a higher degree of risk build-up or substantial changes in investor sentiments about the market are condensed out with darker colours, for such extreme conditions are scaled with strong prior gauges in the SOM process.

Figures 5.7, 5.8, 5.9 and 5.10 depict the dynamics in crisis maps, with splicing of the sample time frame to semiannual crisis maps produced each time from the signed spillover gauges, which show the evolving vulnerability in the changing networks. Since the first half of 1998, the Asian financial crisis spurs a complicated web of fissures connecting networks that emerge, corresponding to a crisis. We find coverings open up, outlining vulnerability surges from Asia to the European markets, Australia and China. Additionally, fissures creep up along the Greek crisis to the OEE markets across the plateau, forming an italic 'v' shape. The picture that emerges may reflect the effects on these economies of the slowdown of global resource trade with Asia. This complex feature begins to ease out in the first half of 2001, forming fissures that give a parabolic pattern running across the entire plateau. A key to this visualisation is this pattern, predominant in all calm periods, forming ground water mounds running from end to end. In the advent of a crisis, we find that, in keeping with our analogy, coverings open up and the flash storm (i.e., unprecedented shocks) gives rapid dissipation of ephemeral ground water mounds into lower discharge areas. In other words, new depressions in the plateau underscore vulnerability transmitting from sources to predominantly less vulnerable markets. In such circumstances, the common parabolic pattern in the fissures become less visible. We outline some of such changes in the local topographic depressions

In the first half of dotcom bubble, a stream passes through a crevasse with a significant void. This is evident in the OED plot axes and continues right up across AC and GC until the latter half of 2002, shifting the crevasse carrying stormwater from the AC to GC blocks in the axes.

Facing the USA mortgage-backed securities crisis, the fissure changes shape from the common parabolic pattern to the italic 'v' pattern, and is also found earlier during the Asian financial crisis. This highlights the predictive power of the changing shapes on the plateau, indicating imminent, large-scale crises. As the crisis emerges into a full-scale global crisis, the bedrock in our plateau (analogous to systems of VAR) becomes riddled with openings. From a bird's eye view, the topographic depressions indicate the sheer fragility of the entire plateau, reaching a melting point corresponding to global meltdown.

The parabolic pattern in the fissures is lost again with European crisis emerging in 2010. The plateau cracks open, creating a new crevasse with significant voids from GC continuing right up to the OED markets. The parabolic pattern in the fissures re-emerge in early 2011, and remain up until late 2014 when the topography begins to change shape. Since early 2015, cracks and sinkholes continue to open up in the areas underneath the parabolic pattern with a new web of fissures creeping up unlike before. Although it seems the dislodging of the bedrock is more severe in the OED to AC and in the AC to OED and GC, late 2017 especially shows a complete melting point with deep cracks running all across the plateau. Next, we try to discover whether investors' access to information precede crevasse formation by using a similar analogy with the information transmission maps.

5.4.6 Information transmission maps

According to Wilcox and Fabozzi (2013), the complex network of feedback loops in interconnected financial markets is naturally disguised by frictions in the system. The issue of erratic market operations leading to the build-up of systemic risks across, not only investments but also multiple investors, is better understood through the collective sentiments of a network of investors. The essence of this network is that the system is acyclical and, hence, has signals (e.g., the many types of information that investors use as a 'rule of thumb' to take selling and buying decisions, including expected returns on investment, asset prices, trading volume and expected credit worthiness) that naturally pass through intermediaries. In doing so, the signals that are transmitted out of these channels are overlain with frictions, as those intermediaries may choose to transmit signals that accumulate above a threshold. This leads to similar directions in investors' actions. The resultant investor herding behaviour amplifies the effect of a positive feedback loop, which can be considered a contagion of investors' actions. Moreover, together with the lack of an early warning approach that makes anticipatory control ineffective and the risks borne out of the investors' collective actions, the erratic explosions in the corresponding investor activity turns systemic. Consequently, the system is introduced with bubbles and crashes (Wilcox and Fabozzi, 2013).

Now we may explain how this environment leads to an adverse feedback loop. According to Davis et al. (2010), a shock causes a decline in economic activities with an adverse feedback loop. The loss of asset values and decline in profits result in increasing default rates in the real sector and an amplification in loan losses for the intermediaries. Hence, the drag on the buffer of resources that intermediaries can drawdown with the falling markets, contributes increasing business cycle volatility and the tightening of liquidity available in both the market and real sector. Consequently, what follows is a further drop in asset values and profits, sending the sector into a downward spiral.

All this provides us with a natural foundation from which to investigate and visualise an information transmission (i.e., signal with frictions) pathway with investors' changing degree of risk tolerance. This may allow us to predict the crisis transmission pathway, forming a possible early warning system. In what follows, we present dynamic $SOM^{information}$, and examine if we can derive crisis generation indicators that correspond with SOM^{crisis} presented earlier.

Again, drawing on the analogy of a plateau with mid-colours and occasional lighter-coloured higher features, the interpretation of $SOM^{information}$ is somewhat different than the interpretation for SOM^{crisis} for two reasons. First, there is an immense network of fissures running wildly across the plateau with $SOM^{information}$. This suggests that market participants are always riddled with intense information, regardless of crisis or calm periods. Hence, those speculators with a lack of knowledge may analyse crisis predictions differently, generating positive and adverse feedback loops as well as reinforcing cycles. Second, a crevasse would indicate collective risk tolerance resulting from varying levels of intermediation and signal processing by speculators, indicating that liquidity is being drawn out of the markets. In contrast, risk-taking is analogous to a crevice in our discussion, which may precede a crisis or may deepen as a crisis unfolds. This is because while amplifications in signals represent risk aversion, risk tolerance is highlighted by a dampening in the neutrality index. Hence, despite the common parabolic pattern of fissures in the plateau housing the smaller crevices and gaping crevasses, the interpretations may change entirely for the maps in figures 5.11, 5.12, 5.13, 5.14.

In the second half of 1998, burrows and crevices are at the bottom left corner of the $SOM^{information}$ topography, highlighting that the risk tolerance of Asian investors dominates AC markets during this period. In the subsequent period, the first half of 1999 depicts reinforcing cycles in risk aversion sentiments followed by risk-taking in the developed markets (OED) coming about from the Asian investors. Both these periods accord well with the SOM^{crisis} topography outlining crisis transmission from the AC to OED markets. The shifting of portfolios from the crisis-ridden Asian markets to the OED markets shows new corresponding crises transpiring in the OED markets, consistent with the active hedging phenomenon and leading to elevated market linkages (Kodres and Pritsker, 2002; Kocaarslan et al., 2017).

Facing the dotcom bubble, emerging deep crevasses running across the OED region on the top left corner of the plateau scar the topographic formation. This portrays the dampening of risk tolerance that corresponds to events unfolding in the OED markets, and may lead to the riskier allocation of assets, as suggested by Kocaarslan et al. (2017). This in turn, raises the prices of risky assets, emanates investor-based contagion and may also lead to new crisis formation in the SOMcrisis maps. This is especially apparent in the first half of 2001. As the SOM^{crisis} maps show, Asian investors pulling investments out of the OED markets correspond to a gaping new crevasse creeping up in the OED zone. Hence, the predictability between the SOM^{crisis} maps and $SOM^{information}$ maps provides us with the early warning system for which we aimed. This also holds for Lehkonen and Heimonen (2014) theory that in crisis periods, homogeneous information transmission triggers active hedging, leading to frequent asset reallocation. This, in turn, induces interdependence. Additionally, this process addresses a crucial network problem. The maps lay out the role of Asian investors in propagating a crisis emerging from the OED cluster into the EC cluster, and underscores the importance of a middle node in transmitting a crisis from A to B.

Both the $SOM^{information}$ and SOM^{crisis} maps revert to somewhat a similar parabolic pattern, which is slightly more wedged in for $SOM^{information}$ maps, which continues until the onset of the GFC. During this period, a yawning crevasse runs across the OEE markets, highlighting a high level of risk intolerance for mostly the Middle Eastern markets that coincides with the greatest turmoils, including war breaking out in this region with the US-led Iraq invasion. This is of no surprise; such events would force investors to pull resources out, and the emerging pattern depicts this loss of risk tolerance.

With the dynamic maps rolling into the periods marking the advent of the GFC, the bottom right corner of the plateau begins to form a twiggy crevasse that opens up into a dark void, signifying the full cycle of the GFC. As the GFC subsides, the crevasse fills up, resembling the very beginning of its formation before disappearing completely. During this period, the bottom left corner of the $SOM^{information}$ maps depict visible topographic depressions as holes and burrows. Here again, we draw on an analogy to the changing dynamics of patterns in risk tolerance that $SOM^{information}$ illuminates. The imminent GFC, which can also be observed as the scars forming up on the SOM^{crisis} landscape, marks a time of high-risk evasion in the OED markets and risk-taking among European and Asian investors. It is possible that the realisation of crisis fear among investors. Eventually, the GFC swings into full cycle, forcing OED investors to become risk-takers while European and Asian investors become risk averse following a flow of capital out of the OED into the EC and AC markets. This results in gaping crevasses creeping up across the EC and AC markets located in the SOM^{crisis} maps in the latter half of 2007, as the heightening sense of potential crisis in this region transmits crisis into these markets.

The mere visibility of the scars opening up in the $SOM^{information}$ maps, along with the transpiring European debt crisis, creates deep crevasses running across the GC and OED markets in the SOM^{crisis} maps. With the Greek austerity measures taking effect, these crevasses fill up, corresponding to the deepening of scars into new crevasses in the $SOM^{information}$ maps. This suggests that investors across the GC and OED markets resort to dodging risk, leading to amplifications in crises in 2010 as observed in the SOM^{crisis} pattern. Investors become risk-takers again as the crisis subsides. This continues up until the second half of 2012, when investors eventually begin to avert risks again confidence as builds up in the GC and OED markets. Consequently, this triggers another phase in this crisis across the affected markets, as investors pull resources out. Risk tolerance reaches its minimum for the GC and OED markets in the first half of 2016. These patterns are consistent with the feedback loop argued by Wilcox and Fabozzi (2013) and Kocaarslan et al. (2017), who showed that a crisis does not subside despite investors becoming risk averse. Investors react by making risky investment decisions, which pushes the already high prices of risky assets even higher and assumes lower returns than risk. As a result, the second half of 2016 scars the plateau with widening crevasses and deep sinkholes. This time crisis is predominant in the OED markets, and is transmitted to other markets and the area adjacent to the GC markets to form multiple reinforcing cycles that affect Asia more than the other markets.

The outcome of the maps produced in Figures 5.7, 5.8, 5.9, 5.10, 5.11, 5.12, 5.13, 5.14 is further reinforced in Tables 5.1 and 5.2. Both these tables provide additional insights, as they display the summary statistics of 900 basis classification indices generated from the risk perception matrix and signed spillover (vulnerability) matrix. Combining the results from both these tables, it is evident that an amplification in risk tolerance precedes crisis generation. Moreover, amplification in the vulnerability of markets heightens risk tolerance, forming a diabolic feedback loop. An agent-based diabolic feedback loop is concentrated out for 1998, 2001, 2002, 2003, 2004, 2006, 2007, 2008, 2009, 2011, 2012, 2013, 2014, 2015 and 2017. The efficacy of the method's predictive capacity is laid out in the prediction segment of these tables. These tables show that in the periods immediately before crisis amplifies, investors with public information attempt to prevent investment losses by pulling capital out of the markets. Coupled with fire sales and the depreciating value of cross-border assets, this reinforces a worsening spiral in market. Therefore, these findings provide evidence for the significance of our approach as an early warning system.

In summary, we have observed that deciphering the $SOM^{information}$ maps helps us to make predictions in the SOM^{crisis} maps, and both the systems feed off each other. Hence, these models connect well to deliver us an early warning system. This system allows us to devise and interpret one model to make predictions on the other.

5.5 Policy implications

What is most appealing about both the 'crisis maps' and 'information transmission maps' is that they show the changing dynamics in vulnerability corresponding to risk tolerance within a system of markets in a readily accessible manner. Although we are able to extract important information related to the intertwining nature of the markets and risk tolerance across these markets with DY and signed spillover analysis and signed risk aversion computed from a structural VAR framework, the 'crisis maps' propose complementary information that outlines a vulnerability transmission pathway. When presented along with the information transmission stream flowing out of the collective sentiment in investor networks, these results lay out a pathway for vulnerability transmission. Hence, we present an early warning system of contagion without having to exploit systemic risk estimates.

It is important to acknowledge, that while regulators have little control over crisis transmission, there is more control over information transmission, and a unique way to curtail crisis is to know the right intervention for information transmission.

We contribute an additional tool in the arsenal of policymakers and active portfolio managers who are willing to take pre-emptive steps. The web of fissures across the system results from a cascade of shocks emerging out of an origin and travelling on via the network of fissures in the system (e.g., Greece to China to Australia). Understanding this association is key to taking appropriate actions in short circuiting a crisis. For example, instead of taking a more drastic approach, such as by blocking a pathway through outright bans on short selling or capital movement restrictions, regulators can take a more moderate approach, such as by controlling news borne out of mere speculation or syndication, which may probably stop a crisis from happening in the first instance.

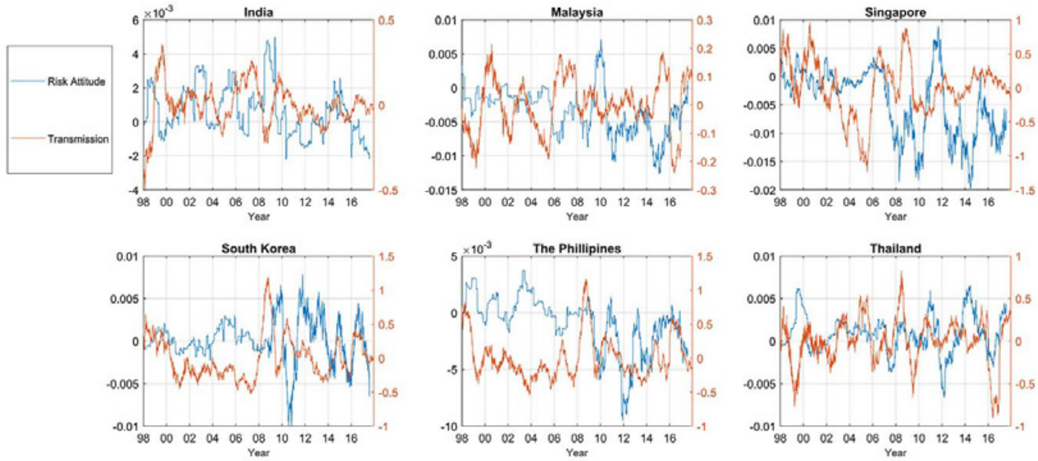
In other cases, suddenly emerging sinkholes suggest a high degree of vulnerability for an individual market or group of markets to shocks from a small set of sources. Thus, a domestic response to the cause of the crisis may involve repairing macro-economic fundamentals with traditional approaches, as proposed by Eichengreen et al. (1996); Eichengreen and Hausmann (1999) and Bordo et al. (2001).

5.6 Conclusion

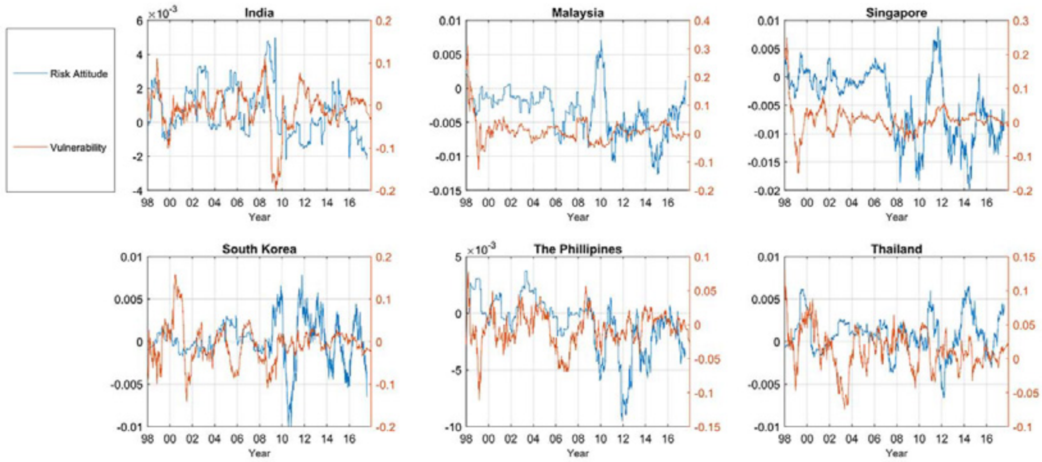
In this chapter, we have made multiple contributions to the systemic risk literature, especially concerning means through which to drive pre-emptive policy responses. This has always been key to systemic risk studies, in that there lies a potential for subduing a crisis in its early stage. First, we presented signed spillover connectedness between markets across crisis and calm periods, laying out not only the degree of changing dynamics in the vulnerability for a system of markets but also the direction of vulnerability and transmissions in the intertwined financial markets. Second, we presented risk tolerance gauged with unsigned systemic risk as a covariate. This suggests that investors' collective decision-making is driven by existing or speculated crisis in that system, which reinforces crisis. **We further examined the robustness of this analysis by testing the significance of the risk preference index across time**. Third, we presented the changing dynamics in the crisis propagation pathway across the sample markets over time, laying out maps of contagion transmission. Finally, we provided patterns that emerge with risk tolerance, which are analogous to a public information transmission pathway, that also complement the degree of investor-based contagion existing in a system. In comparing the features of the two dynamic mapping approaches, we presented an early warning system making predictions on an emerging crisis without essentially needing a crisis estimate. We do not necessarily propose a simple system to decipher, and indicate the system is more effective with the availability pre- and post-crisis data. Instead, we propose a system that allows control over potential crisis propagation without supervisors having to directly intervene in market operations.

In the aftermath of the GFC, policymakers came together in realising the importance of identifying vulnerability to crises originating elsewhere and in coordinating actions to prevent such transmissions León et al. (2017). Our aim was to convincingly implement a means by which regulators can restrict the flow of asymmetric information by simulating the effects of alternative intervention paths and identifying the points of most effective intervention in the information channel. By doing so, regulators may devise proper interventions to dampen feedback effects within a holistic associated network and, as such, may circumvent the full brunt of a crisis. The success of such interventions is largely due to the responsible processing of information by intermediaries and investors who manage investors' collective resources and, hence, the potential for sending an economy towards a downward spiral.

5.7 Figures & Tables

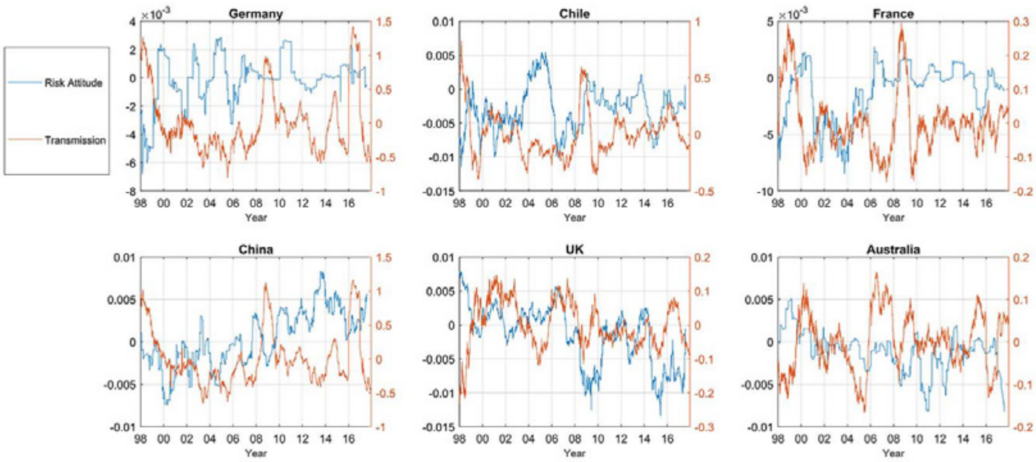


(a) Asian crisis markets with transmission

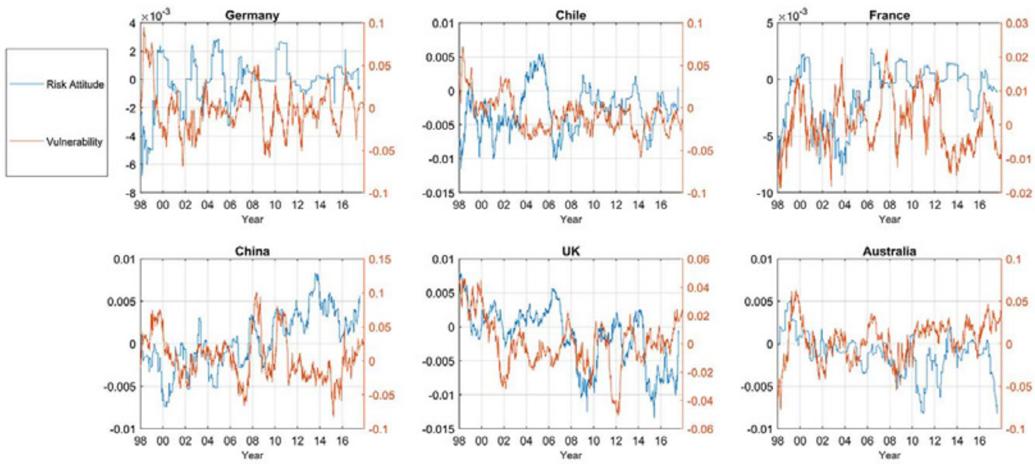


(b) Asian crisis markets with vulnerability

Figure 5.1: Asian crisis markets

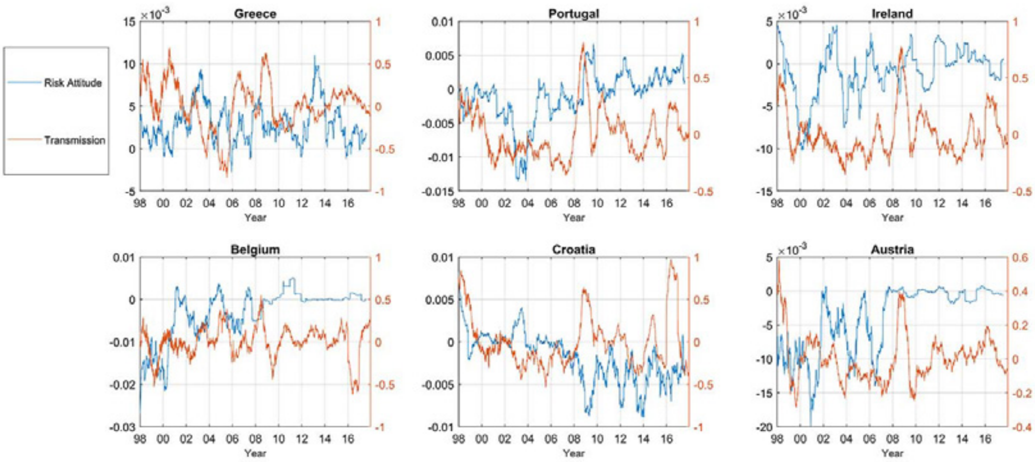


(a) Export crisis markets with transmission

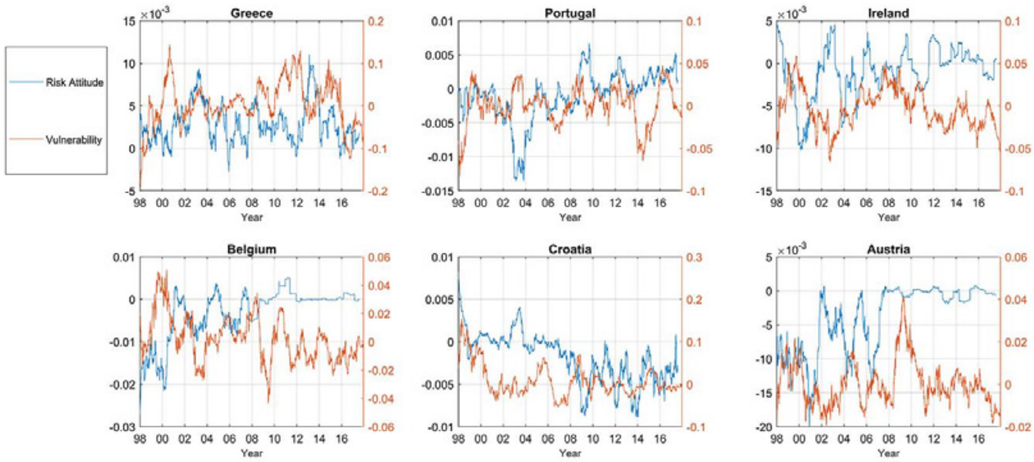


(b) Export crisis markets with vulnerability

Figure 5.2: Export Crisis Markets

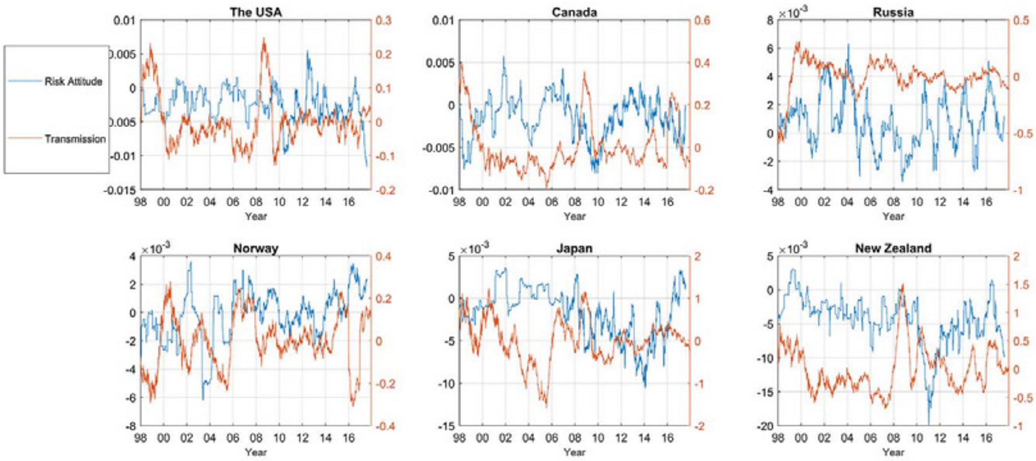


(a) Greek crisis markets with transmission

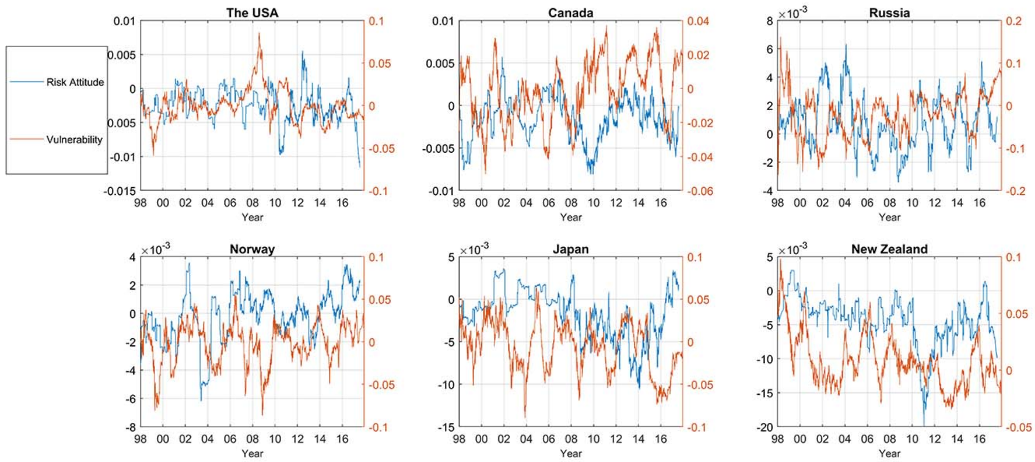


(b) Greek crisis markets with vulnerability

Figure 5.3: Greek crisis markets

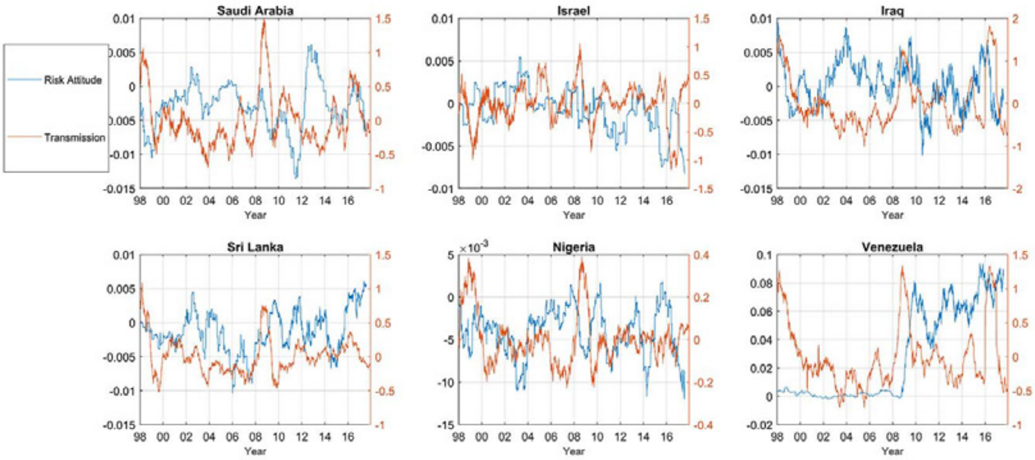


(a) Oil exporting developed markets with transmission

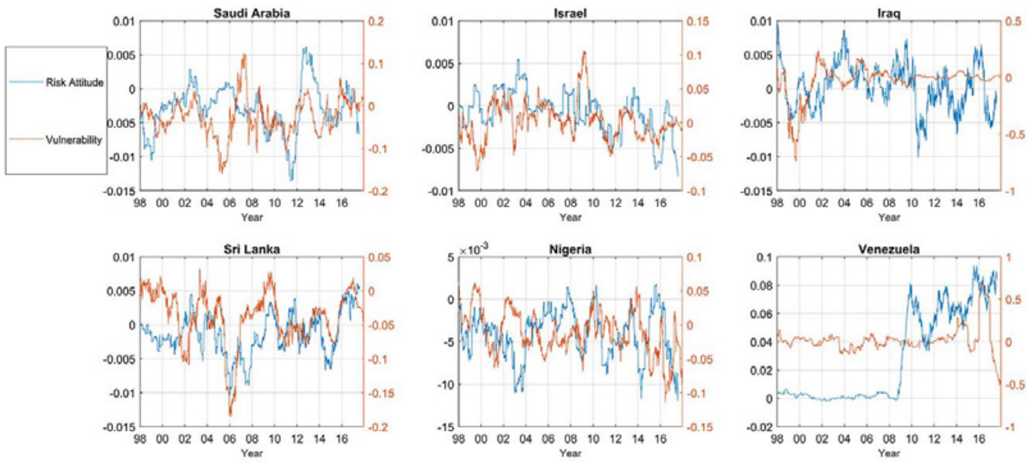


(b) Oil exporting developed markets with vulnerability

Figure 5.4: Oil exporting developed markets



(a) Oil exporting emerging markets with transmission



(b) Oil exporting emerging markets with vulnerability

Figure 5.5: Oil exporting emerging markets

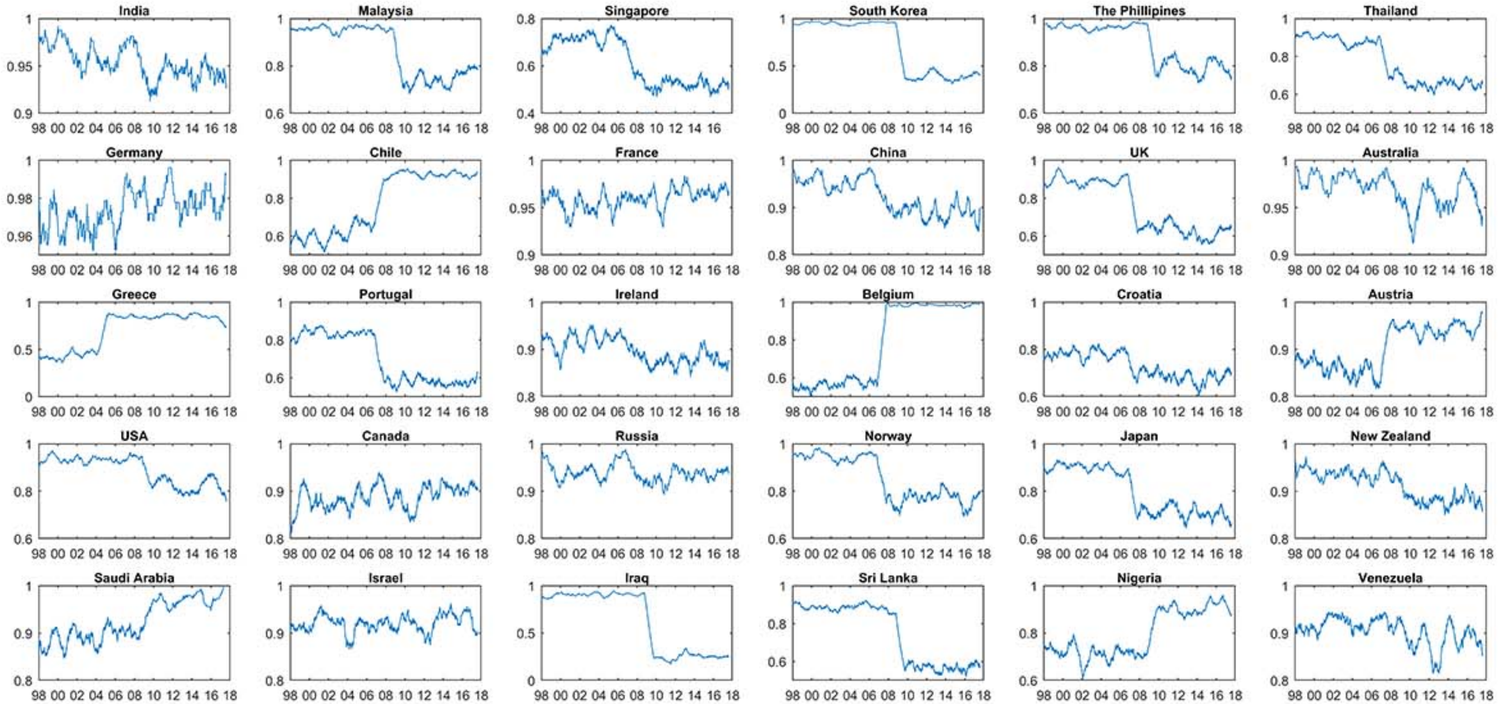
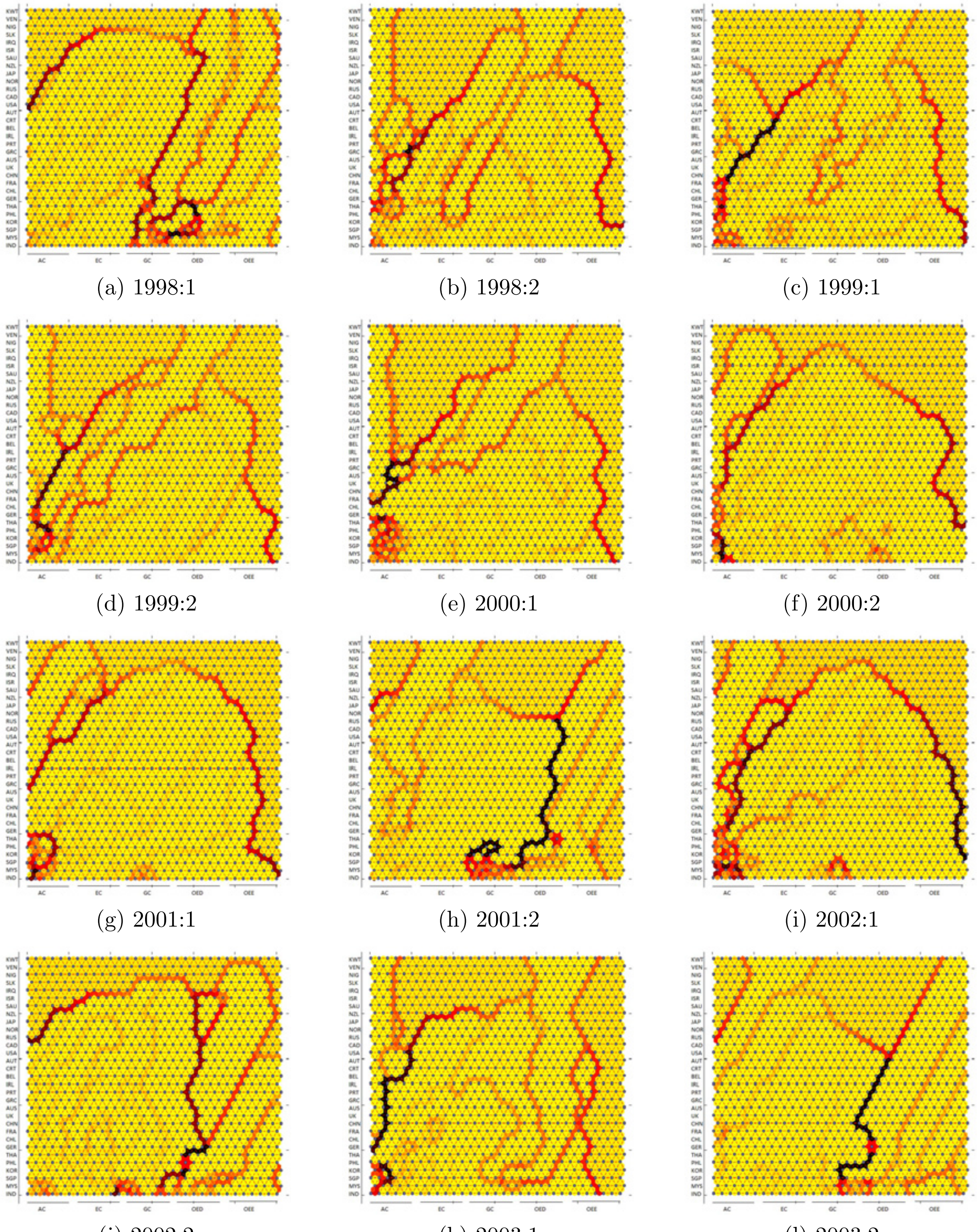


Figure 5.6: The Wald test results for risk neutrality. This plot shows Wald significance test outcome across time, with no risk preference in the null and risk aversion or risk taking as alternatives



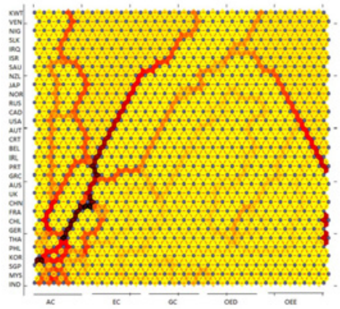
(a) 1998:1 (b) 1998:2 (c) 1999:1

(d) 1999:2 (e) 2000:1 (f) 2000:2

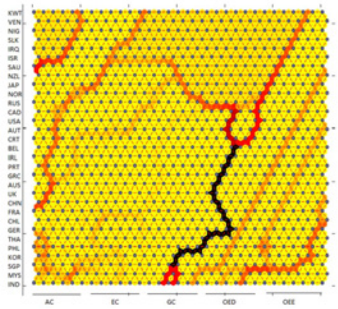
(g) 2001:1 (h) 2001:2 (i) 2002:1

(j) 2002:2 (k) 2003:1 (l) 2003:2

Figure 5.7: Dynamic crisis transmission maps from 1998-2003



(a) 2004:1



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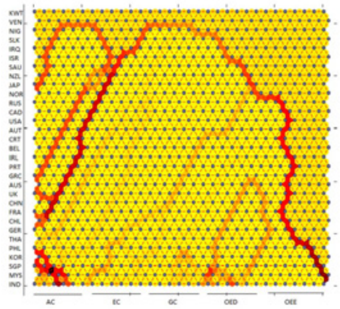

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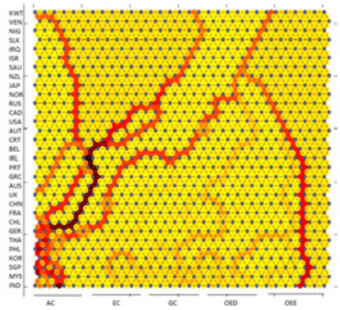

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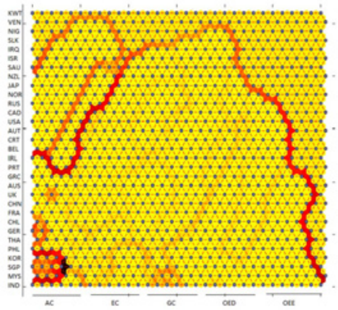

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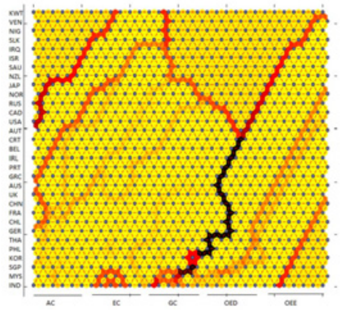
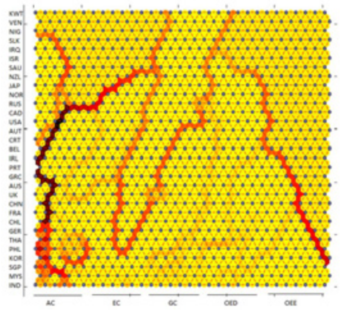


(f) 2006:2



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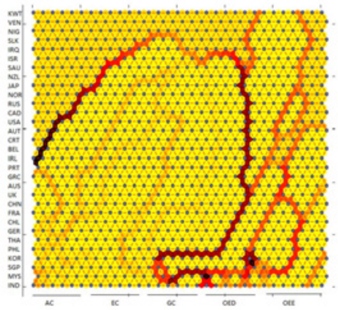
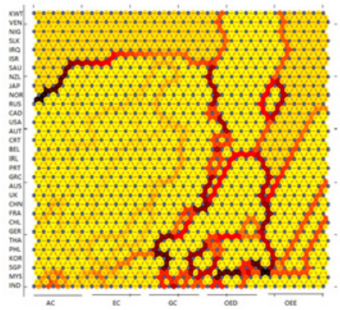
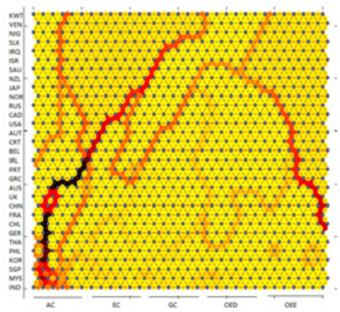


(h) 2007:2



(i) 2008:1



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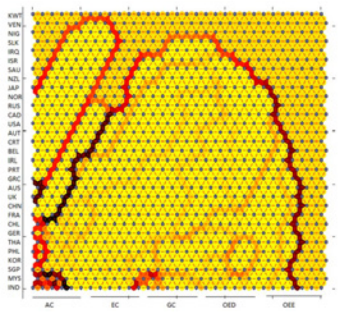

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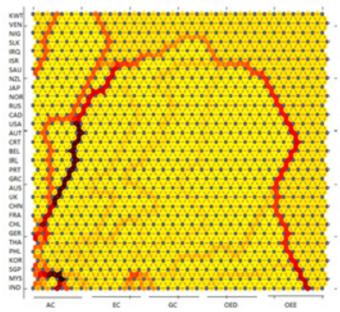
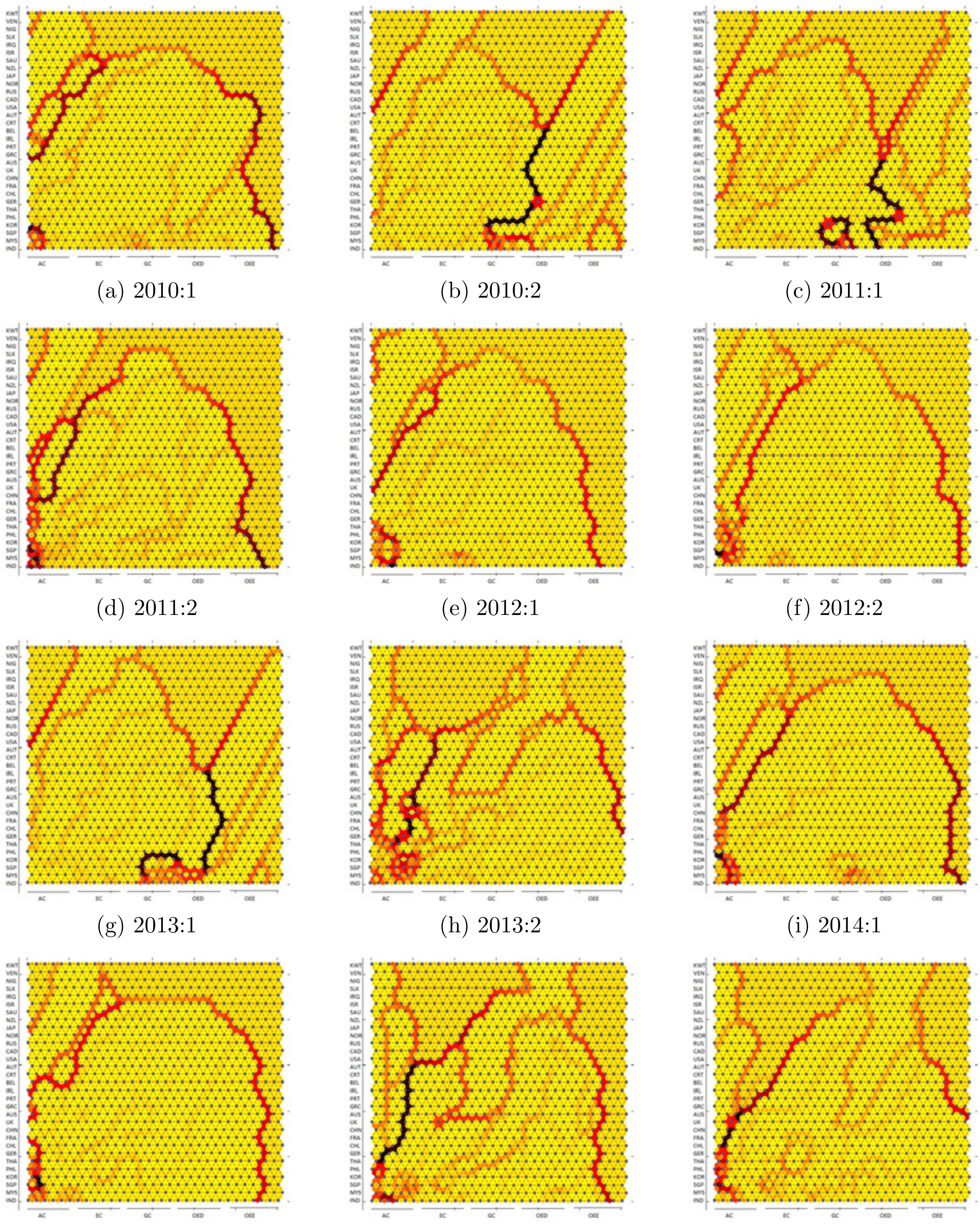


(l) 2009:2

Figure 5.8: Dynamic crisis transmission maps from 2004-2009



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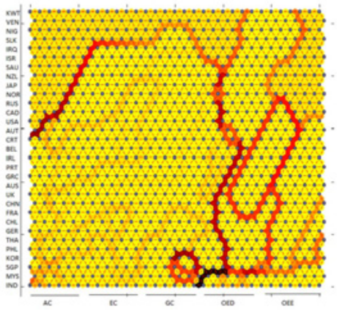
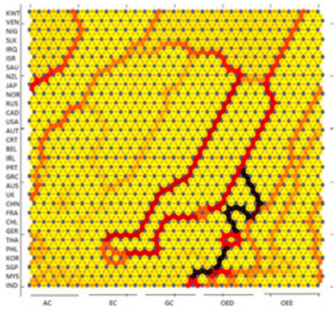
(g) 2013:1 (h) 2013:2 (i) 2014:1

(j) 2014:2 (k) 2015:1 (l) 2015:2

Figure 5.9: Dynamic crisis transmission maps from 2010-2015



(a) 2016:1



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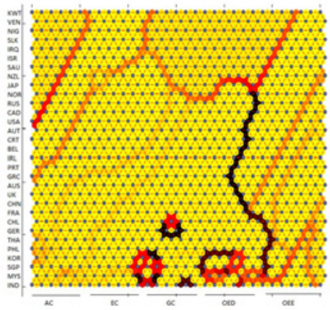
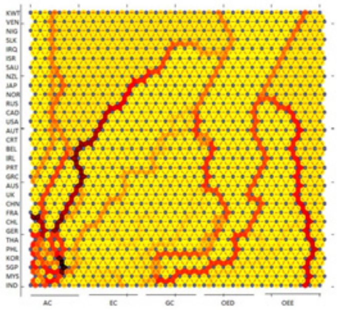
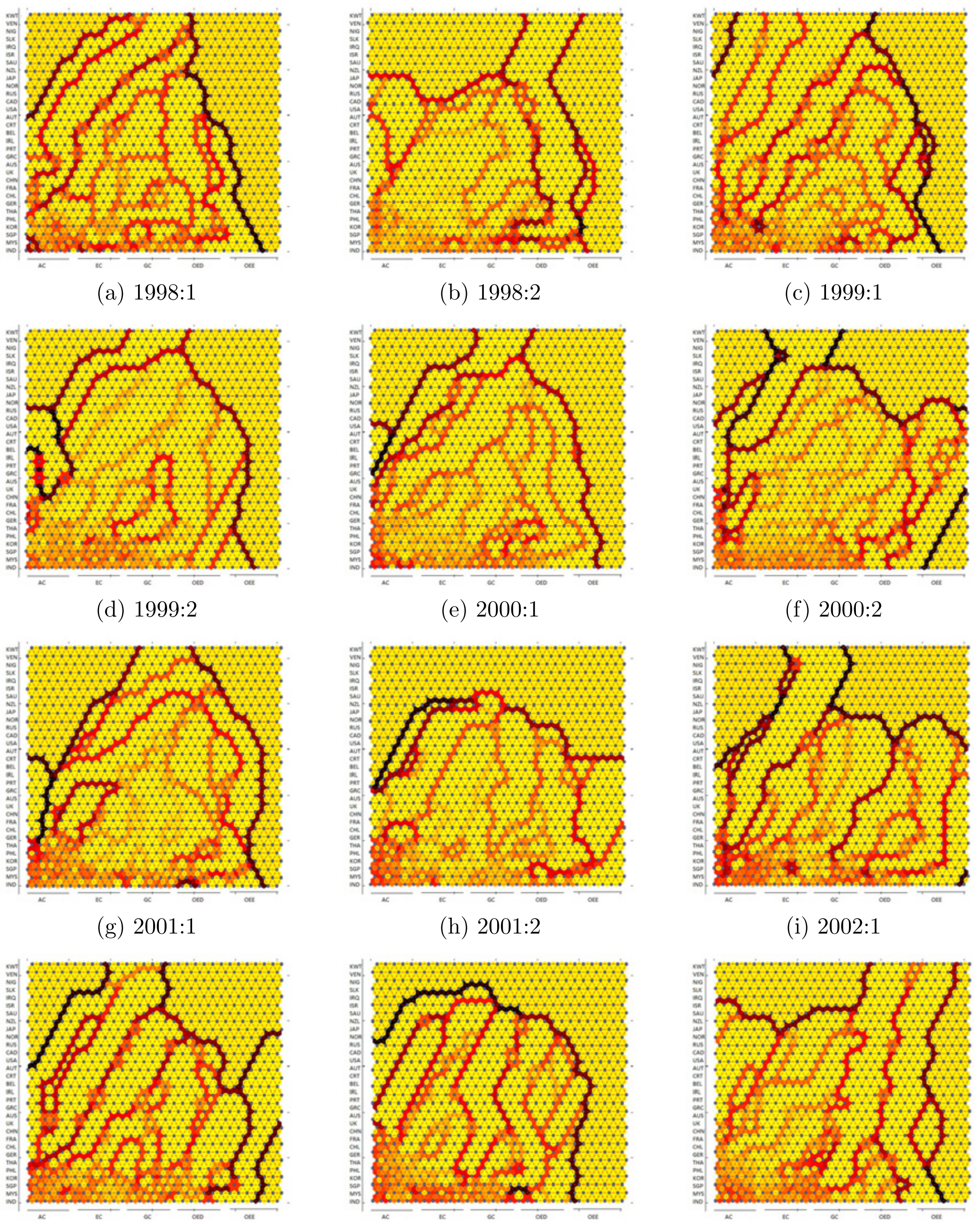


(c) 2017:1



(d) 2017:2

Figure 5.10: Dynamic crisis transmission maps from 2016-2017



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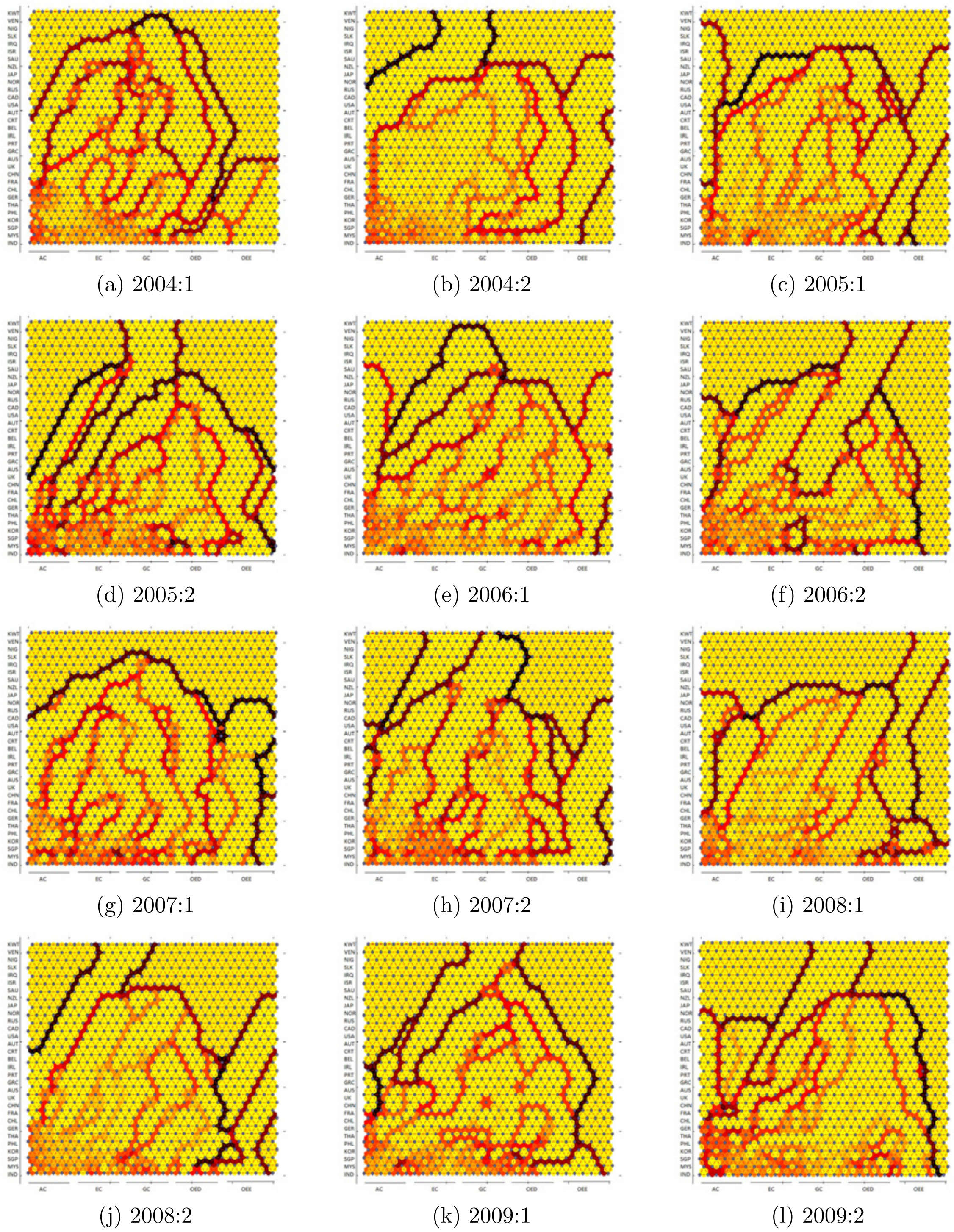
(g) 2001:1 (h) 2001:2 (i) 2002:1

(j) 2002:2 (k) 2003:1 (l) 2003:2

Figure 5.11: Dynamic information transmission maps from 1998-2003



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(g) 2007:1 (h) 2007:2 (i) 2008:1

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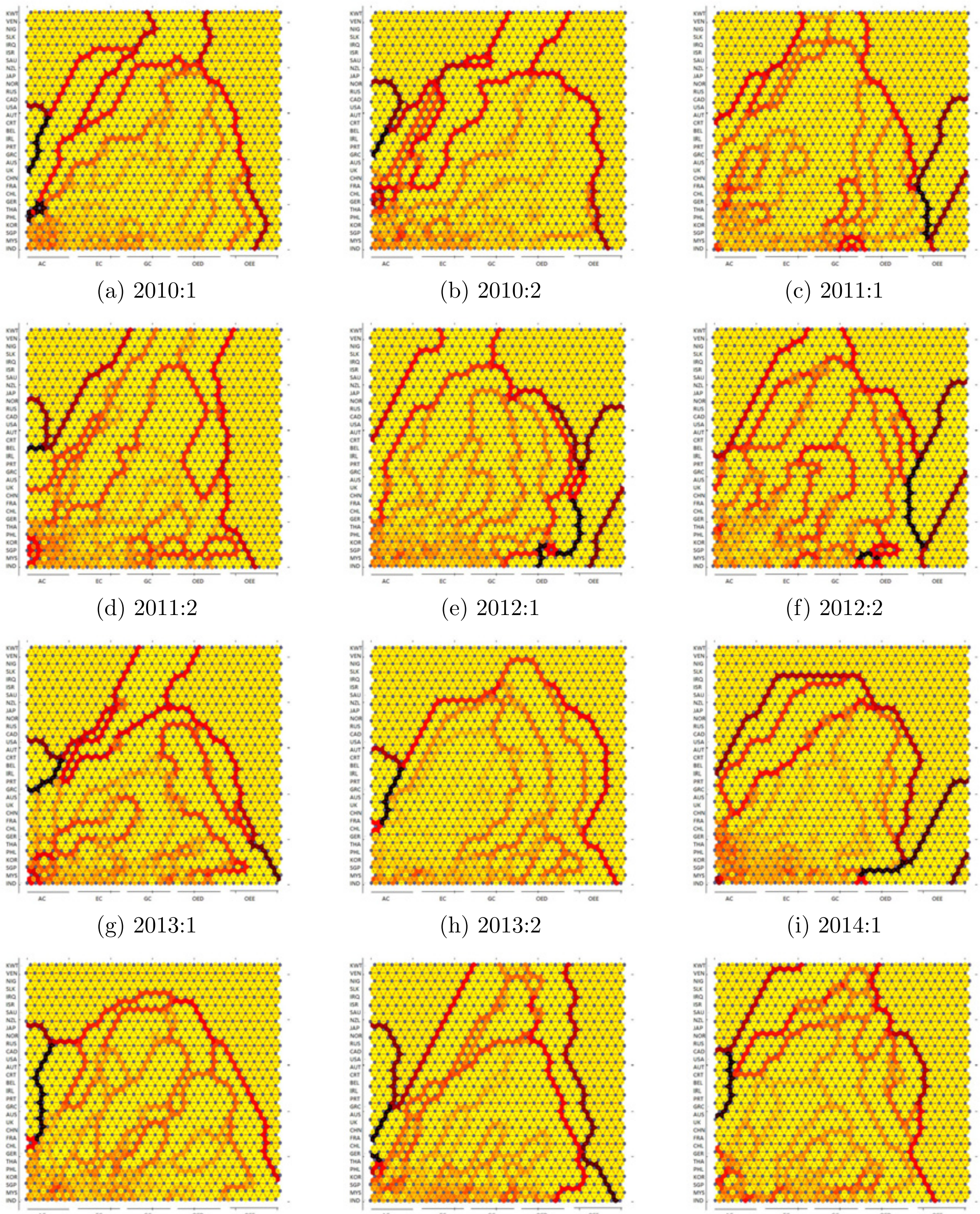
Figure 5.12: Dynamic information transmission maps from 2004-2009



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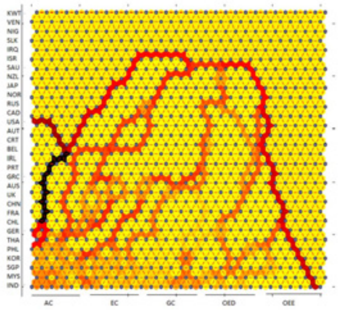
(d) 2011:2 (e) 2012:1 (f) 2012:2

(g) 2013:1 (h) 2013:2 (i) 2014:1

(j) 2014:2 (k) 2015:1 (l) 2015:2

Figure 5.13: Dynamic information transmission maps from 2010-2015



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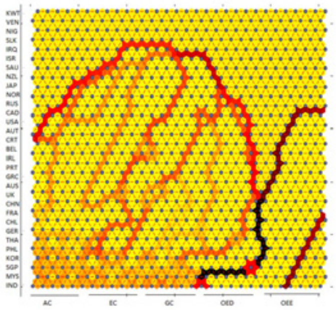
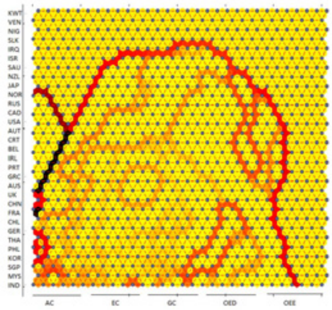
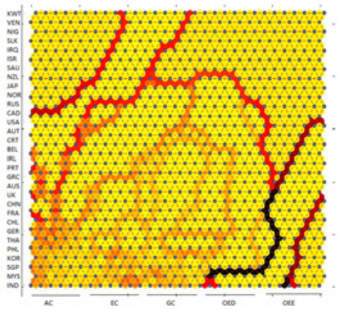


(b) 2016:2



(c) 2017:1



(d) 2017:2

Figure 5.14: Dynamic information transmission maps from 2016-2017

Table 5.1: Summary statistics of 900 basis investors' risk perception classification

Actual	1998:1	1998:2	1999:1	1999:2	2000:1	2000:2	2001:1	2001:2	2002:1	2002:2	2003:1	2003:2	2004:1	2004:2	2005:1
Min.	4.00	5.00	6.00	3.00	13.00	13.00	3.00	33.00	10.00	2.00	24.00	10.00	16.00	7.00	34.00
1st Qu.	214.0	194.0	190.0	242.0	191.0	207.00	219.0	275.0	207.0	275.0	281.0	262.0	192.0	190.0	336.0
Median	441.0	415.0	444.0	528.0	409.0	422.0	465.0	472.0	426.0	434.0	463.0	441.0	394.0	423.0	528.0
Mean	**471.0**	463.8	462.9.2	511.1	437.1	451.6	**479.2**	**494.4**	443.7	**492.8**	482.7	**485**	452.1	455.6	**545.6**
3rd Qu.	744.0	712.0	716.0	744.0	647.0	689.0	727.0	703.0	692.0	721.0	688.0	743.0	716.0	732.0	800.0
Max.	956.0	957.0	954.0	957.0	955.0	952.0	957.0	960.0	939.0	959.0	952.0	961.0	953.0	956.0	952.0
Actual	2005:2	2006:1	2006:2	2007:1	2007:2	2008:1	2008:2	2009:1	2009:2	2010:1	2010:2	2011:1			
Min.	26.00	5.00	5.00	6.00	3.00	21.00	3.00	8.00	26.00	16.00	10.00	3.00			
1st Qu.	172.0	200.0	207.0	232.0	271.0	207.0	247.00	214.0	258.0	190.0	257.0	185.0			
Median	378.0	382.0	462.0	430.0	579.0	432.0	435.0	492.0	526.0	380.0	471.0	411.0			
Mean	408.6	428.6	**469.5**	473.6	**525.6**	461.9	478.3	483.5	**506.4**	428.8	504.6	420.0			
3rd Qu.	529.0	629.0	695.0	727.0	756.0	716.0	709.0	744.0	748.0	672.0	799.0	630.0			
Max.	960.0	957.0	946.0	957.0	960.0	952.0	960.0	955.0	957.0	959.0	960.0	952.0			
Prediction	2011:2	2012:1	2012:2	2013:1	2013:2	2014:1	2014:2	2015:1	2015:2	2016:1	2016:2	2017:1			
Min.	14.00	27.00	6.00	6.00	22.00	8.0	6.00	5.000	5.00	1.00	6.00	28.00			
1st Qu.	229.0	175.0	180.0	260.0	242.0	230.0	201.0	205.0	199.0	247.0	228.0	261.0			
Median	422.0	371.0	462.0	505.0	471.0	479.0	440.0	414.0	471.0	441.0	458.0	440.0			
Mean	**465.7**	430.7	463.2	**491**	476.9	**484.3**	467.5	456.8	**490.4**	483.6	460.9	**477.8**			
3rd Qu.	717.0	647.0	705.0	727.0	723.0	765.0	752.0	678.0	805.0	744.0	658.0	695.0			
Max.	957.0	957.0	958.0	957.0	957.0	952.0	956.0	951.0	956.0	951.0	960.0	947.0			

Table 5.2: Summary statistics of 900 basis signed risk classification

Actual	1998:1	1998:2	1999:1	1999:2	2000:1	2000:2	2001:1	2001:2	2002:1	2002:2	2003:1	2003:2	2004:1	2004:2	2005:1
Min.	4.00	1.00	2.00	1.00	12.00	10.00	10.00	1.00	1.00	14.00	14.00	9.00	6.00	1.00	2.00
1st Qu.	215.0	282.0	230.0	200.0	216.0	240.00	267.0	203.0	298.0	240.0	206.0	262.0	283.0	230.0	280.0
Median	461.0	508.0	507.0	500.0	435.0	488.0	457.0	454.0	533.0	519.0	472.0	501.0	533.0	426.0	573.0
Mean	476.9	**495**	497.5	482.9	435.4	475.9	480	461.4	**520.2**	491.8	**468.7**	507.7	**513.5**	459.1	513.8
3rd Qu.	748.0	708.0	761.0	716.0	646.0	708.0	710.0	720.0	748.0	716.0	728.0	761.0	762.0	701.0	714.0
Max.	961.0	944.0	961.0	959.0	955.0	951.0	948.0	945.0	959.0	961.0	941.0	961.0	946.0	957.0	957.0
Actual	2005:2	2006:1	2006:2	2007:1	2007:2	2008:1	2008:2	2009:1	2009:2	2010:1	2010:2	2011:1			
Min.	11.00	8.00	2.00	11.00	1.00	6.00	5.00	3.00	6.00	1.00	2.00	22.00			
1st Qu.	250.0	174.0	247.0	243.0	236.0	227.0	250.00	198.0	257.0	228.0	202.0	238.0			
Median	500.0	360.0	510.0	505.0	496.0	481.0	499.0	372.0	496.0	484.0	461.0	420.0			
Mean	491.4	482.4	485.5	**493.6**	475.3	**491.2**	**485.2**	428.8	**486.8**	471.1	458.9	443.8			
3rd Qu.	713.0	701.0	714.0	722.0	697.0	758.0	745.0	716.0	726.0	699.0	693.0	679.0			
Max.	953.0	961.0	940.0	939.0	960.0	956.0	959.0	961.0	956.0	959.0	956.0	939.0			
Prediction	2011:2	2012:1	2012:2	2013:1	2013:2	2014:1	2014:2	2015:1	2015:2	2016:1	2016:2	2017:1			
Min.	6.00	20.00	1.00	1.00	1.00	18.0	11.00	1.000	5.00	1.00	5.00	16.00			
1st Qu.	231.0	259.0	233.0	259.0	247.0	243.0	279.0	293.0	234.0	227.0	247.0	287.0			
Median	462.0	483.0	474.0	506.0	535	491.0	496.0	513.0	505.0	432.0	410.0	492.0			
Mean	489.6	**495.2**	464.7	492.2	**506.8**	493.3	491.2	511.3	498.9	455.6	446.9	**512.7**			
3rd Qu.	767.0	746.0	679.0	748.0	770.0	746.0	713.0	699.0	762.0	697.0	669.0	752.0			
Max.	961.0	936.0	958.0	945.0	958.0	952.0	961.0	959.0	961.0	960.0	961.0	945.0			

Chapter 6

Conclusion

6.1 Summary of findings and implications

In the current thesis, we aimed to address long-standing questions from the contagion and systemic risk literature, and attempted to model crisis from our proposed methodology. The main purpose of the thesis was to discover common patterns among past crises, that is, a contagion pathway. **This will allow regulators to better control a crisis through: (i) interventions; (ii) detect contagious or more resilient candidates across a sample of over 30 important international equity markets; and (iii) predict crisis using a potential early warning system, which precedes a crisis or a mutually reinforcing cycle.** The novelty and significance of this study is that while it allows regulators to contemplate their own market's position in the intricate web of networks connecting all markets, it also provides a means for regulators to prepare for economic spirals well before they emerge. The methods also allow managers of risk to yield better returns, which minimises their investment's susceptibility to counterparty risk.

In the second chapter, we reviewed the extant literature that examines the symbiotic relationship between systemic risk and contagion. We discussed systemic risk and contagion encompassing important studies from past to present. We also discussed crucial tenets from the current real sector, including financial networks, stress testing, shadow banking and securitisation. We elaborated on studies concerning mutually reinforcing feedback loops that precede a cascading financial sector. We discussed investors' risk appetite from the behavioural science perspective and in conjunction with the rational expectation theorem. We focused on the importance of dynamics in investors' changing risk preference in crisis escalation. Most importantly, we provided insights into the gaps in the extant literature that we aimed to address in the current thesis.

In the third chapter, we began by examining alterations in the core peripheries of a complex network consisting of over 30 international global equity markets across crisis episodes spanning over two decades. The important novelty lies in the predictive visual pattern proposed in this chapter, enabling regulators to simulate effects of multiple intervention pathways to contain a crisis.

- We drew a filtered network from static weights generated with popular GVD to identify the contemporaneous position of important markets in an intricate network of systemic risk. We found Germany, the USA, Russia, Belgium and similar advanced economies to be the highest transmitter of crisis in major episodes of turmoil. Conversely, we showed Canada, Australia, China and the UK are the most vulnerable in similar instances. While it is interesting to visualise how some equity markets distance themselves better than others, a complete market dynamics could not be drawn from such networks.

- Next, we investigated the markets with dynamic analysis produced to DY spillover indices. Crucially, we found equity markets primarily affected by the Asian financial crisis (in our AC cluster), including India, Singapore, South Korea, the Philippines, Thailand and Malaysia demonstrate better resilience to global shocks. We explained the reasons for such trait. First, the markets are disproportionately connected to each other, and due to varying industry composition and governance risks are often diffused better than in advanced markets. Indeed, the dynamics are very different for this part of the world compared to other advanced economies. We examined these markets more closely. India's large stock exchange in terms of number of companies issuing shares, which diffuses the concentration of risk in the Indian markets. Singapore has the largest financial centres in the region, and holds most of its cross-border asset portfolios with China, Korea and others within the region. Thus, its exposure to advanced economies is offset by its exposure to developing economies. In contrast, Australia holds significantly more shares issued in the USA, European Union, which is similar to Japan, while Japan invests heavily into Australia because it considers Australia its gateway to the Asia–Pacific. Additionally, Australia holds substantial cross-border liabilities with the USA and European Union, and is thus highly exposed. Nonetheless, this creates a vicious loop, especially for Australia in terms of its degree of vulnerability to Western economies, concerning the third- and fourth-order peripheries.

- Then, we were faced with a crucial question: 'Does cutting off links with important peripheries helps in subduing an imminent crisis?' By turning links off between important peripheries indiscriminately, we found transmission and vulnerability both spikes respectively for developing and advanced economies, with the exception of connections to the USA. Conversely, unlike Japan or Malaysia, Australian market's vulnerability escalates when connections to the USA is turned off. We conjecture that turning links off never produces better results.

- Understanding market susceptibility does not sufficiently allow regulators to manage risk propagation. We proposed a novel predictive pattern to allow regulators to visually simulate a contagion pathway and decide where effective intervention should lie. Our dynamic crisis maps contributed to the extant literature by providing means of predicting a potential crisis by drawing mutually reinforcing feedback loops beforehand. The emergence of feedback loops that precede a crisis is visually discerning and proposes a novel early detection method. We provided an additional contribution to the literature by finding a common pattern in contagion spanning over two decades. This yielded a very important piece of information: contagion patterns do not alter dramatically after all.

Important issues prevail regarding DY spillover measures. For example, knowing about the changing degree of risk cannot sufficiently allow us to model crisis. Further, unless we untangle the direction of risks, the absolute value representation of weights in the adjacent matrices may lead to mis-identification of crisis affecting a market. Hence, we progressed by introducing a novel signed spillover measure in the fourth chapter.

In the fourth chapter, we introduced this novel measure based on MHD to more information regarding time-varying systemic risk measures. The important novelty of this chapter is that we propose a new method, which evolved from earlier decomposition methods, that allows us to identify markets that we consider contagious.

- We began by comparing the dynamics of systemic risk spanning across our sample markets over two decades with both signed and DY spillover analysis. We found that signed spillover indices produce information that DY spillovers often fail to detect due to their absolute representation. For example, DY spillover matrices show excessive resilience building for South Korea, Singapore, the Philippines, China and Israel. DY spillovers also detect heavy transmission building from markets such as Venezuela, the USA, Nigeria and Greece that are normalised with signed spillover matrices. We provided a rationale for the signed spillover measures that produced a better outcome. First, South Korea and Singapore hold the highest cross-border asset portfolios of the advanced economies. These markets are far less resilient due to their exposure compared to their neighbouring countries' markets. The conflict in Middle East has driven enough wealth out of the Israeli economy dampening its resilience. In terms of excessive transmission building with unsigned matrices, it is unlikely that even after many austerity measures taking effect in Greece, the Greek market remains a high transmitter. The signed spillover matrices underscore a proper degree of transmission for Greece. This also holds true for Nigeria and Russia. The embargo on Russia in the post-European crisis disentangles the Russian market, so it cannot remain a high transmitter. Conversely, Nigeria was affected by the oil glut that followed Russian embargo, and as such cannot remain a high transmitter. It is well known that the collapse of the Venezuelan economy was one of the great cascades in the recent decade. Thus, it cannot remain a high transmitter. In all, we found our signed spillover analysis models crisis better and produces more crucial information.

- Next, we proposed a novel method to identify the effects of contagion that is free from the effects of instantaneously transitory spikes due to routine volatility evolution. Building on systemic risk estimates, we not only established the symbiotic association between contagion and systemic risk, but also provided a mean to finally detect sources of potential crisis. We found China, Japan, Australia and Singapore become more contagious since the European crisis. While China remains at the forefront of becoming a potential ground zero for crisis, we did not observe China spilling crisis out from the recent domestic market crash. We provided a rationale for a crisis not happening for China, that is, the major cross-border asset portfolio that Hong Kong holds is from Taiwan and the PRC, creating a loop that minimises exposure to markets outside the Chinese jurisdiction. For crises that Australia or Japan do not contract, this is due to their extreme exposure to the USA. Since the severe restrictions on securitisation in the USA that followed the GFC, this has reduced the potential for the USA to trigger a major shock that may amplify the effects on Australia or Japan. Despite this, we now have a better understanding of important peripheries that need attention to dampen potential contagion.

In the fourth chapter, we proposed novel approaches that not only advance our understanding about crisis dynamics but also allow us to detect sources of crisis. Evolving from the fourth chapter, in the fifth chapter, we proposed a model to gauge investors' risk preference indices corresponding to episodes of crisis.

As final chapter of the thesis, we are finally getting closer to producing an early warning predictor that does not require a state-of-the-art crisis demarcation technique to detect a potentially emerging crisis. We proposed a model to identify investors' risk sentiments corresponding to episodes of crisis or potential information regarding an imminent crisis. We produced dynamic information transmission maps that allow regulators to identify points in the public information transmission pathway where the most effective interventions may be implemented to halt the potential for speculative attacks in the market or mere syndication. Thus, we provide a solution to a long-standing issue of knowing how a crisis spreads is not sufficient but one should also know how to stop it.

- First, our model computes investors' risk tolerance by drawing on the same source data we used in the earlier chapters. The risk tolerance indices depict herding induced from potential public information on crisis preceding a crisis and amplifying the effects of crisis. As such, risk tolerance can be a proxy for the public information transmission index. This is also a novelty of this study. We found that Asian investors are becoming more risk-takers in the most recent periods, which is implicit in potentially contagious Asian markets. With the exception of UK and Singaporean investors, those from other markets are more risk neutral. However, erratic behaviour escalates prior to a crisis. Interestingly, when crisis is imminent, investors become risk averse, which explains their reluctance in making new investments. Coupled with fire sales and capital flights, this deepens the effects of an ensuing crisis.

- Next, we contributed to the literature by producing information transmission maps gauged from signed dynamic public information transmission (risk tolerance) indices. We also produced dynamic crisis transmission maps and found predictive visual patterns in the maps when compared to crisis transmission maps. We conclude that immediately before a crisis, investors turn risk averse. Contagion transmission runs along the information pathway and passes through the plateau. Hence, the risk aversion pathway precedes the crisis transmission pathway and provides a means to detect crisis earlier.

This finding allows regulators to short circuit crisis transmission by intervening in the public information transmission pathway. Further, regulators can investigate the potential nature of the information transmission source and manage speculation or planned syndication. The maps make potential information transmission pathways more conspicuous.

Feedback loops are often clouded with market frictions and idiosyncratic shocks. Regarding practical applications, information transmission computed from risk sensitivity is not constrained with idiosyncratic factors involving unobserved frictions and random shocks, proposing a useful tool for crisis detection for regulators. We also addressed major concerns in the literature by producing not only a means to explain how crisis spreads and what causes crisis, but also ways to subdue a potential crisis in a domestic market without needing to convince other foreign peripheries over which regulators of home country often do not have any control.

The phenomenon of heightening risk aversion or dampening risk aggressiveness is analogous to the 'calm before a storm'. This moment of calmness yields a beautiful condition when all the noise in the market slows down. This analogy is portrayed in the words of a poet as

'It's not the moment that it happens,
It's the moment right before,
It's not the rain or crashing thunder,
It's the calm before the storm,
The stormy clouds demand attention,
And the wind can't be ignored,
It's the love of building tension,
Just before the violent storm'

- Kate Dudley

6.2 Limitations and future research directions

The current thesis endeavoured to propose a means through which to discover crisis sources and its transmission pathway, which can be applied practically in the international equity markets. The thesis is subject to some limitations:

- We used daily equity market indices for the period 1998 until 2017 encapsulating 30 episodes of big and small crises. In recent times, there have been several new episodes of crisis that have sent tremors throughout the global financial markets. Future research may expand on the data period and visualise a crisis transmission pathway while discovering feedback loops facing major endogenous and exogenous innovations.

- An important question arises, “what market structure would be consistent with finding the patterns presented in this thesis?” or “Assuming a structural model with homogeneous agents, this assumption would be inconsistent with the cross-sectional heterogeneity implied by different network linkages across markets?” The thesis adheres to the consistency condition set by Romero-Meza et al. (2015), and relies only on country indices to examine the patterns in the thesis. The patterns produce consistent outcome with past crises and make reliable in sample and out of sample predictions. It is very likely that other market structures may produce better and more consistent predictive pattern under some circumstances. We acknowledge that the thesis did not experiment with different market structures in order to identify an optimal market structure for the type of patterns presented in the thesis. In lieu with this, the thesis did not experiment the assumption for cross sectional heterogeneity implied by different market networks. Hence, therein lies a perfect platform for future research, to examine the patterns with different market structures, and with different network structures for consistency.

- In September 2018, the USA markets plunged to new lows when the Dow Jones Index fell by 18.78 per cent and the Shanghai Composite fell to a four-year low at the outset of an escalating Chinese recession. Although the current thesis indicates a potential crisis resurfacing from the Chinese markets, future research may investigate the degree of crisis flowing out of China and into the USA market corresponding to this particular drop in markets. This event provides an opportunity to examine the changing dynamics of Chinese and USA connections to other markets, as securitisation resurfaces and the effects of austerity measures employed at the outset of European crisis diminish.

- The phenomenal global stock market crash of February 2020 triggered by the COVID-19 outbreak set market corrections to new levels, which provide future researchers in a systemic crisis a foundation for new investigations. This ongoing pandemic is a risk that has not built up within the markets, but has caused global stock markets to show a GFC-like collapse. Moreover, the complete lockdown of major economies such as China and Italy and the restrictions in place in other countries have severely disrupted, for example, global supply chains, exports and both financial and non-financial trading. The global rout is expected to heighten economic recessions in both advanced and emerging economies. This unprecedented episode fuels fears and panic in the markets unlike any episodes since the GFC. Future research may examine the information transmission pathway and changing dynamics in investors’ risk tolerance amidst this chaos, and detect if and how this gauges crisis channels facing this new kind of crisis. Most importantly, as this current pandemic is a major crisis that is completely exogenous, the effects are unlike what a systemic crisis yields.

While the source is entirely exogenous and unpredictable, the effects can be well investigated with the means proposed in the current thesis.

- Facing, the coronavirus pandemic, Italy has announced mortgage repayment deferrals; Germany has indicated strict movement restrictions while other European nations move into lockdown; and Canada, the USA and Australia have established stimulus packages to rebound falling markets. The regulators speculate a heightening of sovereign debt risks in their respective countries. More or less, all major economies are preparing for an imminent recession. This provides an ideal natural experiment for research into systemic crisis.

Notably, financial networks may change weights dramatically when gauged on public sector debts (Dungey et al., 2019). Common sense dictates that such instruments in place of equity indices will not alter either the crisis transmission pathway or the information transmission pathway. Future research may examine if investors' risk tolerance predates crisis transmission with sovereign bonds or credit default swap spreads.

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Pacific-Basin Finance Journal 59 (2020) 101255

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

Crisis transmission: Visualizing vulnerability

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ARTICLE INFO

Keywords:
Systemic risk
Networks

JEL classification numbers:
C3
C32
C45
C53
D85
G10

ABSTRACT

This paper develops a means of visualizing the vulnerability of complex systems of financial interactions around the globe using Neural Network clustering techniques. We show how time-varying spillover indices can be translated into two dimensional crisis maps. The crisis maps have the advantage of showing the changing paths of vulnerability, including the direction and extent of the effect between source and affected markets. Using equity market data for 31 global markets over 1998–2017 we provide these crisis maps. These tools help portfolio managers and policy makers to distinguish which of the available tools for crisis management will be most appropriate for the form of vulnerability in play.

1. Introduction

Observed changes in correlation between asset returns during periods of stress have been variously attributed to contagion, spillovers and/or heightened vulnerability of networks. While the literature stretches back as early as King et al. (1994) on spillovers and Allen and Gale (1998) on contagion, the empirical work on networks and systemic risk/connection is more recent.[1] One of the most important predictions of the network literature demonstrates how financial sector networks can become 'vulnerable'. Shocks may spread dramatically via financial interconnectedness as 'vulnerability' affects otherwise 'robust' networks. Empirical representations show how the networks themselves change over time, between calm and crisis periods, and with the development and growth of emerging capital markets; see for example Billio et al. (2012), Khandani et al. (2013), Demirer et al. (2018a) and Chowdhury (2018). The changing nature of the links between institutions can itself be cast as a measure of contagion; see, Dungey et al. (2017), while spillover indices can be obtained from network adjacency matrices proposed by Diebold and Yilmaz (2009).[2]

This paper presents visualization of crisis transmission pathway in a system of financial network via recursive neural networks, largely known as Artificial Neural Networks (ANN). By considering the largest vulnerabilities in the ANN patterns we produce crisis maps which highlight the least resistance shock transmission pathways at any point in time. They are somewhat analogous to slices of

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[1] Systemic risk is the risk inherent in a system of closely connected entities, that can be cast as measure of crisis in the system. That is if triggered, can result in cascading down of the entities forming a global crisis situation. The structure implicit to systemic risk contains the degree of risks transmitted to others from one element and the degree of risks received by the element from others. This allows identification of nodes as either high spreaders or strong receivers within a closed system. The property of receiving shocks from others is closely related to the concept of the varying 'vulnerability' (Allen and Gale, 2000; Gai and Kapadia, 2010; Acemoglu et al., 2015).

[2] See applications and extensions in Yilmaz et al. (2018); Demirer et al. (2018a, 2018b); Yilmaz (2017); Diebold et al. (2017); Diebold and Yilmaz (2015); Diebold and Yilmaz (2014).

https://doi.org/10.1016/j.pacfin.2019.101255
Received 3 May 2019; Received in revised form 5 November 2019; Accepted 22 November 2019
Available online 23 November 2019

a brain scan lit up by firing neural pathways and as such are easily processed visually. We show how ANN methods relate to the commonly understood VAR representation and hence can be cast as an extension of the vulnerability representations with networks as in Diebold and Yilmaz (2014), Diebold and Yilmaz (2015). The Self Organizing Maps used for this purpose dictates other methods in this area of studies, in that, the maps are produced with a recursive algorithm initiated with random vectors, executing relentlessly until repeating patterns are identified and classified. Self organizing maps are popularized as 'deep unsupervised learning'.

We estimate transmissions from systemic risk estimates, which provides an easily accessible image of the pathways which are most likely to transmit crisis shocks across the system at any point in time. This is used to draw two-dimensional maps of how these pathways change as a crisis, and its associated management plan progresses. Further, we contribute in the vein of early warning literature by presenting in-sample predictions of crisis building in our predefined system.

Our aim is to convincingly implement means by which managers of systemic risk can also simulate the effect of alternative intervention paths in a network and have some knowledge of where the most effective interventions may lie given the structure of the network at any point in time. Although we use existing data, managers may decide to randomize inputs, altering expectations or simply feed the networks with predictions to detect alternative transmission pathways. Thus, we specifically acknowledge the conditional nature of the problem, and that intervention strategies may need to be flexible and time-varying, responding to the changing structure of the network and the many alternative possible sources of shocks.

The literature making use of ANN in systemic risk pattern recognition taking advantage of Self Organizing Maps (SOM) is new. Similar application is found only in Sarlin and Peltonen (2013). The approach allows monitoring of channels of crisis transmission, visualizing of vulnerability patterns in a closed system, and proposes an early warning system for possible crisis transmission effects. Betz et al. (2014) shows that SOM has superior prediction properties than traditional latent models based on early learning systems in predicting crises.

We adapt the SOM approach to include estimated unconditional spillover measures into the crisis map – the original Sarlin and Peltonen (2013) maps are calibrated, rather than drawn from estimated relationships. The crisis maps indicate the propagation of a crisis from one position in the 'state space' to adjacent locations of the financial stability neighborhood, allowing us to map instabilities throughout connected global markets. More generally, the use of crisis maps allow us to connect the ANN approach to existing concepts of financial stability. Earlier papers using ANN for crisis prediction include Liu and Lindholm (2006); Peltonen (2006); Apolloni et al. (2009); Marghescu et al. (2010); Betz et al. (2014), and for network mapping see Barthélemy (2011); Sarlin and Peltonen (2013); and very recently for the clustering of capital markets with SOM, see Resta (2016). Finally, this system enhances our capacity to recognize the direction of induced vulnerability if a crisis ensues. The maps represent a new frontier in the usage of systemic risk and dynamic network estimates.

This paper uses a balanced sample of 31 equity indices.[3] We classify the markets into five clusters based on commonality in their economic indicators or common experiences with crisis. These are identified as Export Crisis (EC) markets – including markets which are heavily export oriented (oil and non-oil); oil exporters in terms of both emerging (OEE) and developed (OED) markets; European markets directly affected by the Greek crisis of 2010 on-wards (GC), high-yield Asia-Pacific countries directly affected by the Asian crisis of 1997–98 (AC). By inclusion of the USA and Japan identified as conduit countries in global literature (BIS, 1998; Baur and Schulze, 2005), we aim to identify conduit effects in the system. The grouping of countries into each of these categories is shown in Table 1. Together with these indices our network incorporates the West Texas Intermediate (WTI) Oil Price Index for the inclusion of oil market conditions.[4]

The sample period covers 1998 to 2017, capturing multiple episodes of financial stress, including the Asian Financial Crisis of 1997–98, the 1998 Russian Financial and LTCM crises, 2000 Dot-com bubble, 2000 Global Energy Crisis, the terrorist attacks of September 11, 2001, the invasion of Iraq in 2003, the SARS outbreak and third global oil crisis in 2003, the ongoing Gaza conflict, the unrest in 2006 through both North Korean missile tests and the eruption of war between Israel and Lebanon also in 2006, the 2008 Global Financial Crisis and subsequent European Sovereign debt crisis; as well as the 2014 Russian crisis and the 2016 Export crisis. Table 1 provides a brief description of each of these events along with the broad dating conventions. Our results also allow us to focus on the potential emerging risk of a crisis centering on China as an important conduit market as proposed in Elliott (2017); Mullen (2017); Quijones (2017); Mauldin (2017); Friedman (2016); Jolly and Bradsher (2015).

We identify the most crisis-prone markets and explain how the impact of innovations in those markets differ from those in markets which are less crisis-prone. The inclusion of oil exporting markets, during periods where conflict affected oil supplies allows us to examine the sensitivity of the global system to volatility and shocks from these sources.

We address six important questions concerning the time varying nature of systemic risk estimates leading to the detection of crisis transmission patterns. First, we examine whether policy interventions which restrict significant transmission paths help inter-connected markets weather shocks. Second, we find that the changing interactions between markets results in changing patterns in risk transmission. Third, we examine whether it is possible to detect which markets are more shock resistant in the sample period from 1998 to 2017. Fourth, we cut individual pairwise links off from the structural parameter estimates and identify if this reduces vulnerability/resilience. Fifth, we produce time varying crisis transmission pathway maps for a predefined system. We illustrate the changing dynamics in risk transmission, and show how this visualization helps to highlight the contemporaneous contagion and

[3] Australia, Austria, Belgium, Canada, Chile, China, Croatia, Ecuador, France, Germany, Greece, India, Iraq, Ireland, Israel, Japan, Kuwait, Malaysia, New Zealand, Nigeria, Norway, Portugal, Russia, Saudi Arabia, Singapore, South Korea, Sri-Lanka, Thailand, The Philippines, the USA, United Kingdom.

[4] We use S&P GSCI Commodity Return Index for commodity inclusion when applicable.

Table 1

Major crisis events. We analyze all events across entire sample period with DY rolling estimates.

Modelling crisis: we summarize important edges found in all conditional spillover figures.

Year	Transmission-markets	Vulnerability-markets	Crisis events
1998:1	Malaysia, The Phillipines, Croatia, Russia, Japan	Greece, Portugal, Ireland, Austria, USA, Japan, Venezuela	1. 1997 Asian Financial Crisis continues. 2. Sourcing from the collapse of Thai baht, resulting in Thailand becoming effectively bankrupt.
1998:2	Malaysia, India, The Philippines, Singapore, Australia, Chili, Norway	Malaysia, Greece,, Portugal, Ireland, Belgium, Croatia, Austria, Japan, Venezuela	1. 1998 Russian Financial crisis-Devaluation of the ruble followed by Russian Central Bank defaulting on its debt 2. 1998 Oil price crash follows
1999:1		Malaysia, The Phillipines, Singapore, South Korea, Greece, Portugal, Ireland, Croatia, Austria, Canada, Russia, Norway, Japan, Iraq, Sri Lanka, Nigeria, Venezuela	Ecuador financial crisis followed by Brazilian Financial crisis and South American economic crisis, effecting many of the GC countries and spreading through the oil markets into Oil dependent countries.
1999:2	USA, Russia, Iraq, Nigeria	Malaysia, The Phillipines, South Korea, Germany, France, Greece, Portugal, Ireland, Austria, Saudi Arabia, Nigeria, Venezuela	1998–1999 Russian Financial Crisis continues.
2000:1	India, South Korea, UK, France, Australia, Croatia, Canada, New Zealand, Israel	Malaysia, The Phillipines, Greece, Portugal, Ireland, Belgium, Croatia, Austria, Saudi Arabia, Israel, Venezuela	1. Early 2000s recession effecting Euroopean Union, the USA (commencing). 2. Japan's 1990s recession (the lost decade) continues.
2000:2		Malaysia, Singapore, Chili, Greece, Portugal, Ireland, Austria, Russia, Saudi Arabia, Venezuela	The dot com bubble leading to dot comm stock market crash, effecting the USA and Canada mostly.
2001:1		Singapore, South Korea, China, Greece, Portugal, Ireland, Austria,USA, Canada, Russia, New Zealand, Saudi Arabia, Iraq, Sri Lanka, Nigeria	The dot com crash continues.
2001:2	Chili, Japan, Iraq, Nigeria	Greece, Portugal, Ireland, Austria, Canada, Russia, Japan, Venezuela	1. Early 2000s recession continues. 2. Japan's 1990s recession (the lost decade) continues.
2002:1	India, Croatia,Japan, Sri Lanka, Nigeria	Greece, Portugal, Ireland, Austria, Russia, Iraq	1. The dot com crash continue.s 2. Japan's 1990s recession (the lost decade) continues.
2002:2	South Korea, Belgium,USA, Canada	India, Chili, Greece, Portugal, Ireland, Croatia, Austria, Russia	1. US Stock marker crash in 2002 followed by excessive speculations prevalent in 1997–2000 led from the September 2011 terrorist attack on US. 2. Enron bankruptcy, Tyco and Worldcom scandals effected energy stocks around the globe emerging from the USA.
2003:1	Singapore, South Korea, Germany, UK, France, Croatia, Saudi Arabia	India, Greece, Portugal, Ireland, Austria, Canada, Russia	1. The dot com crash continues. 2. Japan's 1990s recession continues.
2003:2	The Philippines, Singapore, Russia, Sri Lanka	India, China, Greece, Portugal, Ireland, Iraq, Nigeria	1. Global energy crisis-Increasing tensions in Middle East together with rising concerns over oil price speculations followed by a significant fall of US dollar, resulted in oil prices rise abruptly, exceeding three times the price at the beginning. 2. SARS outbreak: First identified in Guangdong province in China, rapidly took an epidemic form worldwide, slowing down economic interactions with China to many markets.
2004:1	The Philippines, Australia, Chili,USA, Canada, New Zealand, Nigeria, Venezuela	India, South Korea,Greece, Portugal, Ireland, Croatia,USA, Japan, Israel, Venezuela.	1. Global energy crisis continues. 2. The dot com crisis continues. 3. Japan's 1990s recession continues.
2004:2	Croatia, Japan	Greece, Portugal, Ireland, Venezuela	Petrocurrency effect subdues
2005:1	South Korea, China, Iraq	Singapore, Germany, France, Greece, Portugal, Ireland, Belgium, Canada, Russia, Japan, New Zealand, Sri Lanka, Nigeria, Venezuela	1. Global energy market starts to recover. 2. With petrocurrency effect subsiding, this period sees a buoyant global stock markets.
2005:2		Singapore, South Korea, Germany, Australia, Chili, Greece, Portugal, Ireland, Croatia, Canada, Venezuela	
2006:1	South Korea, Russia, Norway,Japan, Saudi Arabia, Saudi Arabia, Sri Lanka	Singapore, Greece, Portugal,USA, Iraq, Venezuela	The GAZA conflict emerges, amplifying the energy crisis.
2006:2	India, UK, Canada, Nigeria	The Philippines, South Korea, Greece, Portugal, Japan	

(*continued on next page*)

Table 1 (*continued*)

Modelling crisis: we summarize important edges found in all conditional spillover figures.

Year	Transmission-markets	Vulnerability-markets	Crisis events
2007:1		India, The Philippines, South Korea, Greece, Portugal, Canada, Japan, Saudi Arabia, Israel, Sri Lanka, Nigeria	Global Financial Crisis (GFC) emerges
2007:2	Thailand, The Philippines, India, The Singapore, South Korea, UK, Australia, Chili, Ireland,USA, Canada, New Zealand, Saudi Arabia, Israel, Venezuela	Thailand, Greece, Portugal, Canada, Russia, Norway, New Zealand	
2008:1	China, Chili, Ireland, Belgium, Saudi Arabia		1. The Global financial crisis continues. 2. Post 2008 Irish banking crisis ensues.
2008:2	India, Croatia	Singapore, Thailand, Australia	
2009:1	Croatia, Austria, Canada, Russia, Norway, New Zealand, Israel, Venezuela	China, Australia, Ireland, Belgium, Japan, Saudi Arabia, Sri Lanka, Venezuela	1. 2008–2011 Icelandic financial crisis leads to credit crisis in UK, hurting the euro-zone areas to some extent. 2. Russian crisis: the great recession in Russia begins resulting in a full fledged economic crisis in Russia. 3. Spanish financial crisis/Great Spanish depression begins. 4. Eurozone crisis/Greek crisis: In the wake of Great recession in the late 2009, several Eurozone members (Greece, Portugal, Ireland, Spain, Cyprus) failed to bailout over-indebted banks and repay foreign debt. 2009–2010 Venezuelan banking crisis unearths.
2009:2	India, Singapore, Germany, UK, Nigeria	China, Chili, Norway	The post 2008 Irish banking crisis leaves German and French banks exposed, having enormous foreign claims in Greece, Ireland, Portugal, Italy, Spain (Greek crisis countries).
2010:1	Belgium	India, The Philippines, Croatia,USA, Canada, Japan, New Zealand, Israel, Nigeria	
2010:2	UK, France, Australia, Portugal, Croatia	The Philippines, Singapore, Venezuela	1. Eurozone crisis/Greek crisis deepens. 2. Spanish financial crisis/Great Spanish depression further fuels in the European sovereign debt crisis. 3. Venezuelan banking crisis continues. 4. Spanish financial crisis/Great Spanish depression continues.
2011:1	The Philippines, Portugal, Japan, New-Zealand	Russia, Norway, Sri Lanka, Venezuela	1. Eurozone crisis heightens. 2. Great Spanish depression contributes in the worsening of Eurozone crisis.
2011:2	India, Belgium, USA, Saudi Arabia, Israel	China, Croatia, New Zealand, Venezuela	Heightening Eurozone crisis, Spanish crisis, Venezuelan crisis reinforces feedback loops across global financial markets, recoupling emerging energy dependent and oil exporting country's markets. This in turn, reinforces risk transmissions back into the USA.
2012:1	Germany, UK, France, Chili, Greece, Austria, Canada	Singapore, South Korea,USA, Japan, Nigeria, Venezuela	Eurozone crisis continues
2012:2	Germany, UK, France, New Zealand, Nigeria	India, Singapore, South Korea, Chili	
2013:1	Greece, Portugal, Ireland, Venezuela	India, Austria, Canada, Norway, New Zealand	Eurozone crisis continues
2013:2	India, Chili, Austria, Russia, Norway	Germany, France, Croatia, Japan	Eurozone crisis continues
2014:1	India, Chili, Austria, Russia, Norway	Germany, France, Croatia, Japan	Commodity price drops with the slowdown in Chinese economy, also contributing into a large scale Brazilian economic crisis.
2014:2	Russia		2014–2015 Russian Financial crisis: Following economic sanctions on Russia, plummeting global oil prices, devaluation of Russian ruble and fire sale of Russian assets all contributed in the development of a major financial crisis in Russia.
2015:1	Greece, Croatia, Austria, Saudi Arabia, Nigeria, Venezuela	Chili, Belgium, Austria, Canada, Norway, New Zealand, Israel, Nigeria, Venezuela	
2015:2	China, Canada	India, The Philippines, South Korea,USA, Russia, Japan	Corresponding to Russian Financial crisis, stock market in the USA starts to decline.

(*continued on next page*)

Table 1 (*continued*)

Modelling crisis: we summarize important edges found in all conditional spillover figures.

Year	Transmission-markets	Vulnerability-markets	Crisis events
2016:1	China, Venezuela	India, The Philippines, Singapore, South Korea, France, Australia, Greece, Portugal, Belgium, Austria,USA, Russia, Norway, Japan, Saudi Arabia, Sri Lanka, Nigeria	1. Export Crisis: Germany, Chile, France, China, UK, Australia among others experience historic decline in total exports to others, followed by the so-called oil-glut. 2. Chinese crisis: A massive drop in Chinese stock markets results in markets terminating transactions in the wake of concerns over a Chinese Crisis, that eventually took the shape of a global meltdown. 3. January 2016 global meltdown resulting from fire sales of Chinese assets brought down the European and the USA stock markets
2016:2		Greece, Portugal, Croatia, Austria, Russia, Japan	
2017:1	UK, Australia, France, Chili, Greece, Portugal, Ireland, Belgium, Croatia, Austria, Japan, New Zealand, Israel, Nigeria, Venezuela	China, Russia, Japan, New Zealand	2016 global meltdown continues
2017:2		China, Australia, Chili, Ireland,USA, Canada, Russia, Japan, New Zealand, Saudi Arabia, Nigeria, Venezuela	

spillover effects using self organizing crisis-maps. Finally, we examine if completing a feedback loop for a cluster spill risks to the other clusters Davis et al. (2010), and hence if prediction of such in the patterns warns us of ensuing crisis in the system.

We find evidence for both increased resilience in the financial networks corresponding to policy interventions in response to a crisis, and previously resilient markets becoming susceptible to newer shocks. This is particularly clear since the European debt crisis. We also find strong evidence of changing interconnections between markets.

We identify the more resilient markets using dynamic networks and crisis-maps. Finally, we show that while spillover indices strongly indicate the possibility of crisis generation in the most recent periods, the crisis maps do not indicate forming a feedback loop and does not result in contagion. This demonstrates the usefulness of the crisis maps in complementing the evidence available from spillover indices.

The paper proceeds as follows. Section 2 presents a brief review of literature. Section 3 presents the empirical framework and Section 5 the data set. The results are presented in Section 6, beginning with the system wide connectedness and the associated network among the markets. This sets the stage for subsequent dynamic analysis. We proceed to develop the crisis-map implementation with SOM. Section 9 concludes the paper with some remarks concerning the role of this new tool in investment and policy decisions.

2. Literature review

Evidence of transmission between markets during crises and the changing size and direction of spillovers poses challenges for diversification and regulatory policy. A substantial literature addresses contagion and volatility spillovers as a mechanism of transmission, particularly in assessing changes in the contemporaneous interdependence among variables (Collins and Biekpe, 2003; Forbes and Rigobon, 2002).[5] A variety of identification approaches to separate contagion, interdependence and volatility spillovers exist (Diebold and Yilmaz, 2015; Acemoglu et al., 2015; Bekaert and Harvey, 1995; Bekaert et al., 2013; Chambet and Gibson, 2008; Eiling and Gerard, 2011; Brooks and Del Negro, 2005; Pukthuanthong and Roll, 2009).

Fernández-Rodríguez et al. (2016) define interconnectedness as a bridge between two crucial visions, 'pure contagion' and 'shock spillover'. Piccotti (2017) argues that there exists a symbiotic relationship in contagion and systemic risk. Endogenous credit and capital constraints turn non-systemic risks to systemic as crisis is propelled through different markets, followed by a reinforcing cycle. The propagation of the crisis itself brings about temporal changes to the aggregate elasticity of temporal substitution affecting asset prices in different markets (Holmstrom and Tirole, 1996, 1997; Kiyotaki and Moore, 1997; Longstaff and Wang, 2012; Elliott et al., 2014; Shenoy and Williams, 2017). Hence, financial contagion increases costs, as the marginal utility of consumption is negatively affected in the short term for long term investors.

Another strand of literature connects the banking and equity market systemic risk transmissions. Myers (1977) describes that as banks and depository financial institutions siphon off large collaterized debts, it drags down all other common equities built into such debt portfolios. This leads to systemic decline in equity indices, and as Hanson et al. (2011) conjectures, the resulting fire sales triggered in the equity market is in effect similar to a credit crunch, which turns a micro level downturn to a macro crisis. The study of

[5] While Collins and Biekpe (2003) define contagion as reversals to net capital flow to an economy, Forbes and Rigobon (2002) argue that the correlation between market returns is largely due to common factors, and hence represents interdependence rather than contagion.

Hanson et al. (2011) cements, that in resemblance systemic markets and systemic financial institutions are not different while facing a global crisis. Diamond and Rajan (2011); Shleifer and Vishny (2010); Stein (2010) further supports this phenomenon by finding intimate connections between credit crunch and fire sale. Among others, Gorton and Metrick (2012); Covitz et al. (2009) cannot distinguish between equity market collapse and a classic bank run on in effect.

Allen and Carletti (2006) outlines that systemic risk does not lead to a cascade if there is proper diversification and no contagion, in both equity markets and in SIFI's.[6] The emergence of a large shock triggers risk transfer between two institutions, two sectors or asset categories (Allen and Carletti, 2010; Billio et al., 2012; Bonaldi et al., 2015; Dungey et al., 2017; Farhi and Tirole, 2017) creating contagion. By definition, contagion is the transfer of systemic risk between two entities or securities, that the conduits connect. This leads to amplification of systemic risk between the entities. Hence, contagion is the catalyst during a crisis that activates systemic risk transmission and vice versa. Khandani and Lo (2011), supports this argument by proposing the 'unwinding hypothesis', that explains systemic risk building in the equity markets with feedback loops forming elsewhere.

Davis et al. (2010) provides empirical evidence of a feedback loop in real sector and asset markets reinforcing a secondary feedback loop in the banking sector forming an enormous adverse feedback loop. Stein (2010) and Hanson et al. (2011) further explains this connection with trenching. Most often, institutional investors rely on short term borrowings for buying trenches of securities. Such trenches of assets are produced by entities such as 'structured investment vehicles' that are often affiliated with banks and depository institutions. Such holdings are used to finance overnight collaterized borrowings in the repo market, in form of 'repurchase agreement', that in turn are used by banks for 'deleveraging', reducing cost of raising capital, leading to the formation of a 'shadow banking system'. According to Stein (2010); Hanson et al. (2011) This 'shadow banking system' is to blame for systemic risks in banks to contribute in developing systemic risks for equities and vice versa. More recently Brunnermeier et al. (2016) provides evidence that in trenching common equities for two banks are build into collaterized debt obligations that are traded in repo markets. In the event of an institutional investors failure to roll over financing, leading to essential fire sales drops the market price for the common equity and in turn reduces the value of portfolios maintained by a different bank located in different countries. Here, a contagion formed within the banks contribute to systemic risk building in equity markets across borders.

It is important to understand that connectedness measures at large do not indicate risk transmission, but identifies the degree of systemic connections, in our case, across borders. Systemic risk transfer within borders may not lead to a full scale crisis, but risk transfer across borders, as Brunnermeier et al. (2016) suggests, may indicate a diabolic loop, or as highlighted in Farhi and Tirole (2017) a deadly doom loop creating a large scale crisis. While contagion measures may capture only the volatility spillovers as suggested in Masson (1998); Khan and Park (2009); Bekaert et al. (2013) that may emerge with large shocks spilling over onto the neighbors corresponding to an event, that is not likely be a systemic event (Dungey and Renault, 2018). We aim to identify the spillovers originating from high degree of systemic risk build up and both the ex ante and ex post development of systemic crisis. This leans more towards financial network studies that is made popular by Dungey et al. (2010b); Billio et al. (2012); Khandani et al. (2013); Anufriev and Panchenko (2015); Acemoglu et al. (2015); Dungey et al. (2017); Demirer et al. (2017) presented in the first half of the paper. The discussion leads to visualization of risk topography approaches of such found in (Duffie, 2013)[7] but we propose a much bigger system. This further contributes to the novelty of the current paper.

Extant empirical work explores the buildup of systemic risk in growing markets which experience pro-cyclical credit buffers and financial crises of varying sizes (Dungey et al., 2007, 2013; Antonakakis and Vergos, 2013; Claeys and Vašíček, 2014). The changes in networks between markets following a crisis period may result in higher shock spillover than previously observed (Acemoglu et al., 2015; Dungey et al., 2005, 2007), some of which may be a consequence of bubbles fueled by credit expansion and associated buildup of macroeconomic vulnerabilities (Kaminsky and Reinhart, 1998; Alessi and Detken, 2009; Drehmann et al., 2010; Drehmann and Juselius, 2014). The recessions resulting from the burst of bubbles are relatively deep and protracted, and features a slow recovery (Jordà et al., 2013; Hermansen and Röhn, 2017).

Cyclical swings in credit conditions lead to varying degrees of crises stemming from systemic risks in the interconnected capital markets (Gonzalez et al., 2017). In turn this has led to concerns over means for reducing the pro-cyclicality of prudential and capital market regulation (BIS, 2010a, 2010b).[8] These concerns have led to a heightened interest in how monitoring capital market interconnectedness may help in early detection of buildup in systemic cyclical risks (Hermansen and Röhn, 2017; Kaminsky and Reinhart, 1998; Alessi and Detken, 2009; Bordo and Haubrich, 2010; Drehmann and Juselius, 2014).

In particular, regulators are concerned that the extent to which shocks are amplified across equity markets is directly related to the degree of vulnerability in the network. We address this problem by examining both transmission and vulnerability.

This paper considers a broad set of global equity indices, investigating their complex interconnections. We build on the growing literature on time varying systemic risks, lying within complex market networks (Giraitis et al., 2016; Diebold and Yilmaz, 2015; Diebold and Yilmaz, 2014) that underpins modern economic network theories (Anufriev and Panchenko, 2015; Glover and Richards-Shubik, 2014). We first make use of the robust DY measure to investigate the contribution of each individual market onto all other markets, and highlight events associated with systemic network instability in the empirical evidence.

In identifying crisis transmission pathway patterns while making predictions on crisis buildup we complement Sarlin and Peltonen (2013); Resta (2016). We propose a 'crisis-map' similar to the map of Sarlin and Peltonen (2013), but compiled with connectedness measures. This is a new use of SOM to better understand risk transmission pathway. Earlier, Duffie (2013) proposed a

[6] Systematically important financial institutions.

[7] Duffie (2013) proposes a 10 by 10 by 10 approach, whereas we progress with a 31 by 30 by 30 approach.

[8] Basel III has been criticized for failing to address the pro-cyclicality of stock markets and crises (Saurina and Repullo, 2011).

risk topography with a 10 by 10 by 10 approach. We countenance Duffie (2013) by proposing a 31 by 30 by 30 approach. In technical terms, the stress topology in the maps are highlighted with a grid of 30 by 30 classification nodes for each data point in the rolled over unsigned systemic risk index across entire sample period, allowing us to visualize a gradual shift to crisis from non-crisis. The 70–30 split of input data into train and test data allows us to incorporate in-sample predictions in the dynamic stress topology, while comparing the crisis occurrences in real time and with unconditional spillover signals.

To our knowledge, no other paper has attempted to detect dynamic stress generation by combining network topology and crisis transmission pathway predictions measured from unsigned systemic risk index.

3. Empirical framework

The Diebold and Yilmaz (2012) (DY) spillover methodology distinguishes spillovers between markets using VAR forecast error variance decomposition (FEVD). The FEVD matrix is used as the adjacency matrix (or 'connectedness matrix') between N co-variance stationary variables with orthogonal shocks; net pairwise return spillovers between assets form the elements of the bi-variate relationships between the markets in a network. The overall spillover index is formed by adding all the non-diagonal elements of the decomposition.

From a VAR(p) of the form[9]

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-i} + \varepsilon_t \tag{1}$$

where x_t is a vector of stock returns, $x_t = (x_{1t}, \ldots x_{Nt})'$, φ_i is a squared parameter matrix and $\varepsilon_t \sim$ N(0, Σ). The corresponding moving average representation is

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i.} \tag{2}$$

in which,

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots + \phi_H A_{i-H}.$$

To circumvent the order variation issue Diebold and Yilmaz (2014) use generalized H-step-ahead forecast error variance decomposition, (where H is user defined), constructed exploiting the generalized VAR framework (GVD) of Koop et al. (1996). This is denoted by $\theta_{ij}{}^{g}(H)$ and given as

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)} \tag{3}$$

where Σ is the variance co-variance matrix, σ_{jj} is the standard deviation of error term for jth equation, A_h is the coefficient matrix in the infinite moving average representation from VAR. At this stage, $\Sigma_{j=1}{}^{N}\theta_{ij}{}^{g}(H) \neq 1$.

Normalizing each row of the adjacency matrix gives

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}. \tag{4}$$

By construction $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$ index captures the full sample static spillover by measuring the sum of off-diagonal elements as a proportion of the sum of all elements as the system-wide connectedness. The directional spillover index identifies variance spillovers of all other markets to market i as

$$S_{i \leftarrow all}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{5}$$

and the reverse directional spillover measures volatility spillover from market i to all other markets similarly as $S_{i \rightarrow all}$, generating $\tilde{\theta}_{ji}^{g}(H)$ parameters.

The net pairwise spillover or pairwise directional connectedness identifies gross shock transmission TO and FROM sample markets. The net spillover between markets i and j is defined as

$$S_{ij}^{net}(H) = S_{i \rightarrow j}(H) - S_{j \rightarrow i}(H). \tag{6}$$

In other words, we compute the transmission and vulnerability matrices from pairwise directional connectedness matrices.

Common network statistics include measures for nodes concerning directional connectedness for links from other nodes as in-

[9] The intercept is suppressed for simplicity and without loss of generality.

degree connectedness and measures of connectedness to other nodes as out-degree connectedness. System-wide connectedness can be measured via mean degree weight measures as in Diebold and Yilmaz (2015).

4. Crisis-map method

With the crisis-map we investigate crisis transmission in global equity indices, by showing how markets evolve during a crisis period. Changes in the location of nodes in euclidean space allows us to identify the possible pathways of lurking crisis in the system.

The self organizing crisis-map makes use of artificial neural network clustering in visualizing the data space. Essentially it implements a non linear projection from a potentially high dimensional input space onto a potentially lower dimensional array of nodes (nodes are also known as neurons in this literature), and as such represents a neural network. In principal, Self Organizing Maps attempt to preserve neighborhood relations by mapping from an n dimensional array of input vectors into a k dimensional array of output nodes. The process applies clustering techniques to assign nodes to their closest cluster via a number of steps. First, a lattice is populated with regular array of randomly generated synaptic weights or centers, in practice initialized with a PCA (Principal Component Analysis) surface. The iterative SOM algorithm, minimizes a loss function scanning across all data points in the input vector, and updates positions on the centers (weights) recursively. The updating process is initiated by reducing the distance, between the input vectors and randomly generated weight vectors, in other words, the loss function. Although, the position of input vectors remain unchanged, the synaptic weights are associated with nodes in the euclidean space. By finding the least distant input nodes from the synaptic weight vectors, we find the least distant nodes with input vectors in the neighborhood space, best known as the "Best Matching Units" (BMU). The algorithm works in neighborhood space, so that closer neighbors have greater weight. This eventually results in a surface of weights resembling a sphere around the lattice. Updating and convergence may be achieved by using the usual gradient descent method. Finally, the non-linear structure of the data is fitted optimally around the lattice, shaping a sphere of clusters, that can be presented in a two dimensional grid of nodes.[10]

In the process of dimensionality reduction with projection and clustering, SOM method also produce robust predictions in the patterns outlined. The process involves moving nodes across Euclidean space: predictors are organised for nodes (say for example equity indices where each return represents a node) and are grouped into intermediate vectors, which in this case are fewer in number than the initial input vectors.[11] In other words, p distinct training vectors, equivalent to intermediate nodes are selected from the input data. Usually, the training data includes at least 80% of the sample data. The problem is represented by two dimensional array of predictions, a process involving random initialization of synaptic weights that we feed into the recursive optimization function, and an updating algorithm until the local minima for the loss function is achieved. The aforementioned updating algorithm leads to output nodes serving as prediction vectors or classifiers in unsupervised clustering. The nodes of the output vectors represent the topology that outlines the structure of the degree of temporal non-linear clustering in the data. The input and output nodes are connected via the weight vectors which project each node in the input vector onto another node in the output vector.

Notably., the iterative backward propagation algorithm has a convergence criterion as it generate weight vectors. Hence, patterns produced in this process are much more robust then contemporary methods of clustering in place.

The process proceeds in five steps producing graphical representation of predictions and classifiers. First, a random weight matrix is generated. Second, the algorithm goes on selecting sets of input nodes and updating the weights via backward propagation (the analytic gradients of the weights construct the hidden layers of edges) and then updating the decay function which governs the relationship with neighbors. In each case the Best Matching Unit (BMU) is found by selecting the Euclidean norms, ε. The convergence criterion provides stability in the projection by centering the ε, that is looking for a total zero error. The visualization initiates at this stage with the decay function identifying sparsely connected nodes.

The neighborhood around the BMU follows an exponential decay function[12]

$$\sigma_t = \sigma_0 exp^{(-t\lambda^{-1})}$$

where, σ_0 is the lattice at time zero, t is the current period and λ is a conditional element. The purpose of the hyper-parameter is to regularize the decay function with penalty for non-convergence, reducing the complexity of the process. In the final stage, weight vectors continuously re-position with neighboring weights changing the most around BMU as reflected by the decay rate. The learning rate ξ decays with $\xi_t = \xi_0 exp^{(-t\lambda^{-1})}$. Here, the one-step ahead weight function is represented as,

$$w_{t+1} = \omega_t + \theta_t \xi_t \varepsilon_t.$$

Finally, the neighborhood meets the convergence criteria (zero in theory), resulting in a lower dimensional response vector. The influence rate[13]

$$\theta_t = exp\left(-\frac{\varepsilon_t^2}{2\sigma_t^2}\right)$$

[10] See Sarlin and Peltonen (2013) for a graphical representation SOM.

[11] The intermediate step offers increased robustness to the crisis-map.

[12] The computational graph of this function takes up a similar structure as that of information processing within our brain neurons, hence the term neural network is loosely used.

[13] This rate substitutes the largely known score function in generalized neural network architecture.

describes the degree of influence for each weight on the convergence. This rate is non-zero for the nearest neighbors to BMU decreasing with distance from BMU.

The neighborhood positions of the clusters in the crisis map represent contagion transmission complementing the approach of Sarlin and Peltonen (2013). In the crisis maps the degree of convergence are illuminated with darker to lighter colored grids resembling none to some degree of ensuing crisis. Failure of convergence indicates heightening of non-linearity between nodes, shown with cracks in the topology.

5. Data

We collect equity market indices from Datastream, pre-process the source data to control for missing values, estimate spillover indices and subsequently use the spillover indices as source data for 'crisis-maps'. Our raw data are daily dollar denominated price indices for 31 equities from Asia, Pacific, Europe, Americas and the Middle East,[14] for the period beginning from 1st of January 1998 up until 15th of September 2017. This period includes at least 10 major episodes of financial stress as documented in Table 1.

We transform the price indices to returns as the first difference of natural logarithms. Following Forbes and Rigobon (2002); Hyndman and Athanasopoulos (2014) we filter estimated returns with 2 day moving average to ameliorate the time zone effect on the data. Essentially, the moving average filter concentrates out the sharpest edge points, reducing white noise. This approach underpins much of the predictive and network literature; see for example Joseph et al. (2017); Zhong and Enke (2017); Elliott and Timmermann (2016); Chen et al. (2016); Ferreira and Santa-Clara (2011); Vaisla and Bhatt (2010); Atsalakis and Valavanis (2009); Cont et al. (2001); Granger (1992); Balvers et al. (1990); Fama (1976); Cont et al. (2001).

Joseph et al. (2017) and Smith et al. (1997) point out that, a moving average (MA) handles discrete time series more subtly than other approaches, despite its simplicity. Hence, we choose the moving average filter for signal processing. The correct choice of window size is important. We conduct multiple trials and find that window size 2 is a more robust choice, complementing the notion of Spectral Windowing presented in Oppenheim and Schafer (2014); Forbes and Rigobon (2002).

6. Empirical results

In this section we present the results from estimating interconnectedness between the 31 equity indices with the transmission pathway outlined in crisis-maps.[15]

6.1. Dynamic analysis

To analyze temporal risk associations among the markets, we construct the DY rolling sample indices to assess both transmission and vulnerability. Following Diebold and Yilmaz (2012) we begin by considering a 100 day rolling window to construct the Diebold and Yilmaz Connectedness Index (DYCI). We choose a 10 day ahead horizon, $H = 10$ for the forecast error variance decomposition, also consistent with Diebold and Yilmaz (2012).[16] We retain the important edges by generating signals with 200 day moving average window.

Since the unfolding of the recent Russian ruble crisis leading to the dampening of global exports, investigations into the dynamic contemporaneous relationship between different markets have flourished (Demirer et al., 2018a, 2018b; Capponi, 2016; Diebold et al., 2017; Diebold and Yilmaz, 2015; Diebold and Yilmaz, 2014; Yilmaz et al., 2018; Liu et al., 2017; Malik and Xu, 2017; Vergote, 2016; Badshah, 2018; Liow, 2015; Andrada-Félix et al., 2018; Ghulam and Doering, 2017; Chiang et al., 2017; Badshah, 2018). We complement these studies by investigating the dynamics in a multi-cluster representation.

We classify the sample markets into Asian Crisis (AC), Export Crisis (EC), Greek Crisis (GC), Oil Exporting Emerging (OEE) and Oil Exporting Developed (OED) markets. We construct individual rolling indices for transmission and vulnerability and present them jointly.

In Table 1, we model all the crisis events across the sample period using DY rolling indices and find rational for important data points. Table 1 summarizes all the important edges in the figures presented in this section. Here we record the spikes in transmissions and vulnerabilities. Most often, a spike would shift the curves up to a new level and the curves remain upstream until a new spike emerges. This can be held also for a curve sliding downstream.

We plot the 'TO' and 'FROM' DY indices for AC & EC, OEE & OED and the GC markets together in Figs. 1–3. Plotting the 'TO' and 'FROM' signals together for transmission and vulnerability allows us to examine whether a higher transmitter also exhibits strong vulnerability; or, if vulnerability is heightened more in response to a local event than a global one. We also examine whether the transmissions and vulnerabilities are counter-cyclical for specific markets. In the following discussion we present a comparative analysis of Figs. 1–3 with effects of oil inclusion in Figs. 4–6. In Fig. 6 we also include commodity compared to oil for investigating potential risks ensuing from Greek Crisis markets in light of findings outlined in the literature.

In all the cases examined, and for the majority of the time period, the transmission estimates are higher than vulnerabilities. This

[14] List of the countries is presented in introduction section.

[15] A section on static networks, counterfactual rolling plots and counterfactual crisis maps are presented in online Appendix.

[16] Diebold and Yilmaz (2012) demonstrate that the spillover indexes are not particularly sensitive to the choice of forecast horizon over 4 to 10 days.

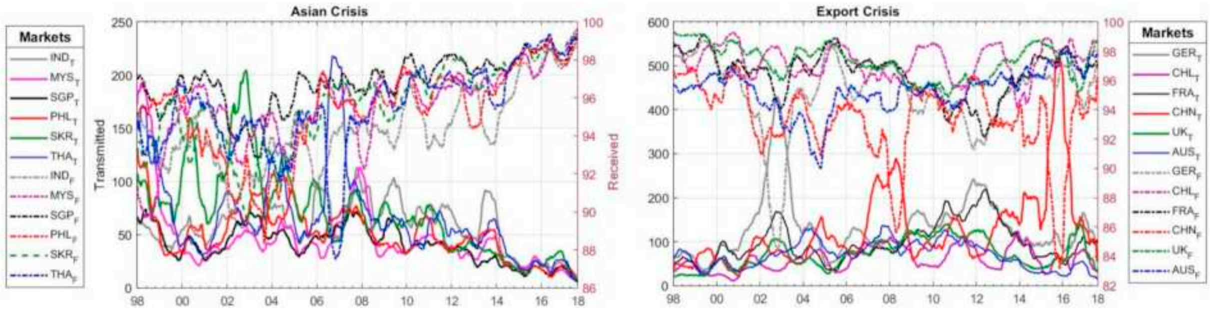


Fig. 1. Asian crisis markets & export crisis markets.
This figure represents a contemporaneous relationship of daily return data for 20 years, for markets categorized within Asian Crisis (AC) and Export Crisis (EC) markets derived from generalized variance decomposition. A detailed description can be found in the 'Asian Crisis' and the 'Export Crisis' subsections under Dynamic Analysis.

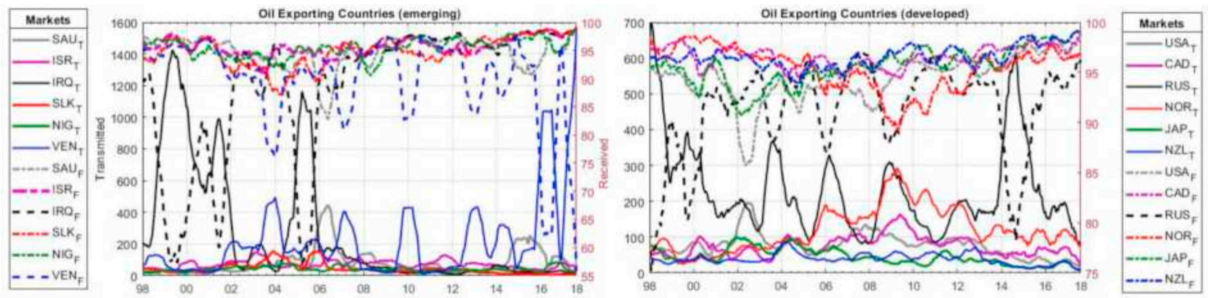


Fig. 2. Oil exporting (emerging) markets & oil exporting (developed) markets.
This figure represents a contemporaneous relationship of daily return data for 20 years, for markets clustered within Emerging Oil Exporting countries (OEE) and Developed Oil Exporting Countries (OED). A detailed description can be found in the 'Oil Exporting markets' and 'Conduit effects' subsections under Dynamic Analysis.

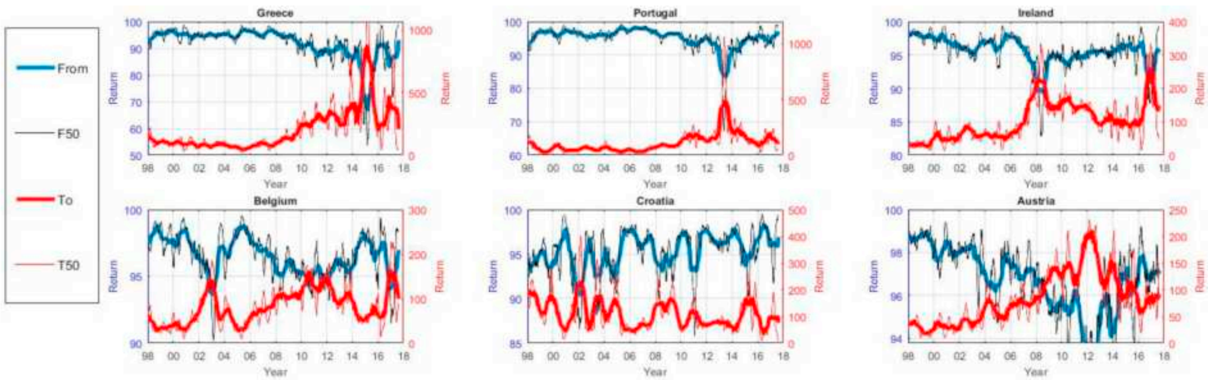


Fig. 3. Greek crisis markets.
This figure represents a contemporaneous relationship of daily return data for 20 years, for sample markets of Greece, Portugal, Ireland, Belgium, Croatia and Austria. A detailed description can be found in 'Greek Crisis' subsection under Dynamic Analysis.
Note: The transmission and the receiving patterns are plot together in all figures, with the same color in both the patterns used for a given country.

points out that usually the contribution of own shock is dominant in explaining variations in any individual market's return, and the total impact of other countries is relatively small. The larger transmissions represent that all the markets are highly interconnected, since the total spillover to all others can be quite large despite individual (bi-variate pairwise) effect on others are relatively small.[17]

The changing interconnectedness of the markets is clear from the results in Figs. 1–3. Periods of crisis are distinguished in each of the panels of figures by a widening of the gap between transmission and vulnerability – transmissions tend to be higher and vulnerabilities – lower. The higher transmissions show when a market experiences crisis conditions it is more vulnerable to transmissions

[17] See Table A1 in online Appendix A.

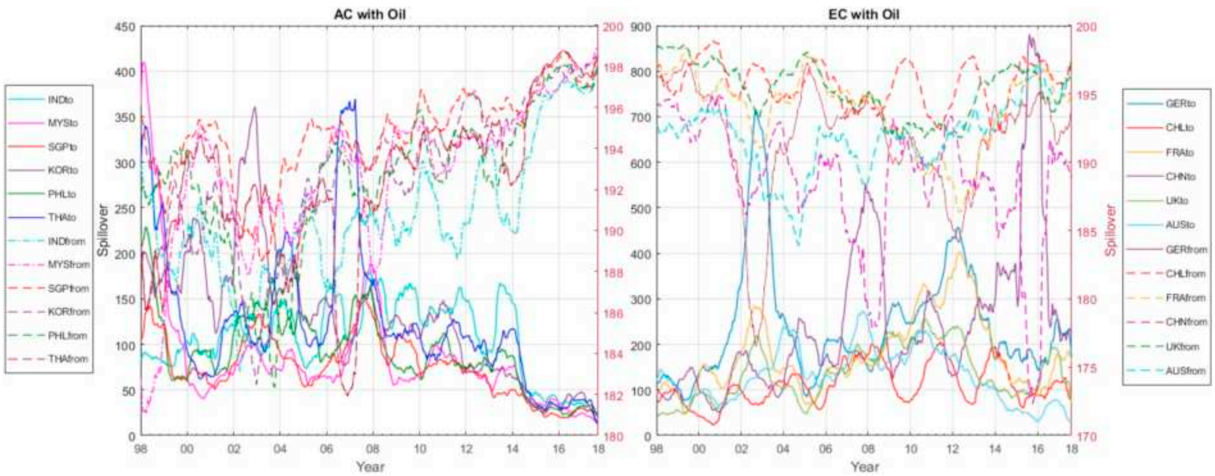


Fig. 4. AC-EC spillovers [oil effect].
This figure represents the conditional spillovers with oil index as exogenous to AC and EC blocks. A detailed description can be found in 'Oil Exporting markets' subsection under Dynamic Analysis.

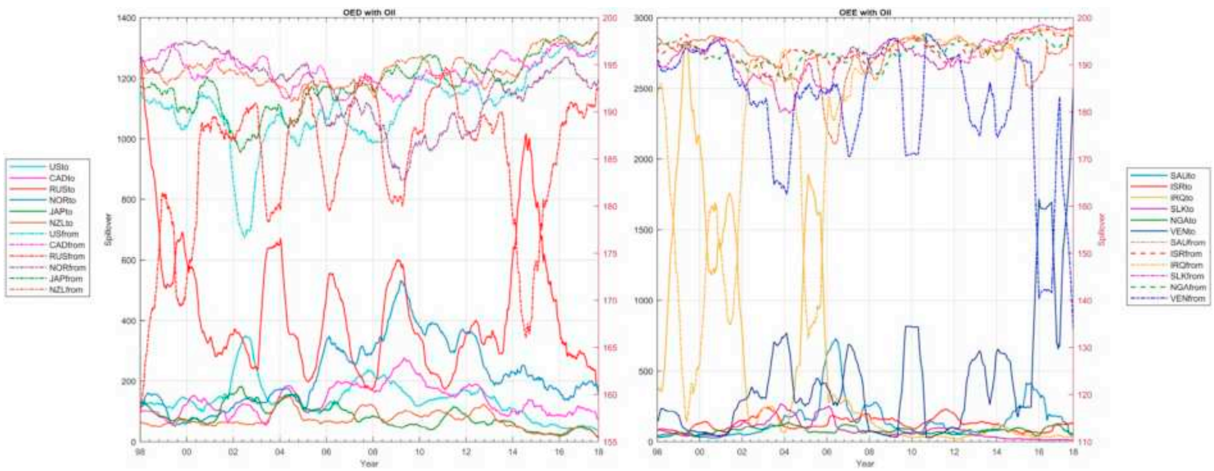


Fig. 5. OED-OEE spillovers with [oil effect].
This figure represents the conditional spillovers with oil index as exogenous to OED and OEE blocks. A detailed description can be found in 'Oil Exporting markets' subsection under Dynamic Analysis.

coming from other markets (this form of increased connectedness is denoted hypersensitivity in Dungey et al., 2010a). The lower vulnerabilities suggest the reduction in the effect of own shocks onto others during periods of turmoil.

6.2. Asian crisis

During the Asian crisis of 1997–98 authorities resorted to different intervention strategies to stem the tide of crisis. Thailand adopted a structural adjustment package; Malaysia moved from a floating to fixed exchange rate regime; Indonesia adopted inflation targeting policy and moved to a floating exchange regime; the South Korean currency devalued and eventually floated, see Khan and Park (2009). Conversely, Singapore retained its managed currency float and China did not intervene.

Fig. 1, shows transmission and vulnerability indices for the AC markets (India, Malaysia, Singapore, the Philippines, South Korea and Thailand). Our focus is on spillover effects, so own effects are excluded from our discussion. The contrast between the signals for Malaysia and Thailand provides a pertinent example of the features attributed to equity markets during the crises. Thailand is commonly viewed as the originator of shocks for the Asian crisis. This is also evident in its heightened transmissions at that time and again in the Global Financial crisis (GFC) period modelled in Fig. 1, during the periods of increasing concerns over feedback effects on its economy. We find that both transmission and vulnerability amplifies for Thailand following the 2006 period. In contrast, Malaysia, was highly affected by the Asian Crisis, despite not being a crisis transmitter. It experienced a large increase in its transmissions at that point followed by decline in the relative effect.

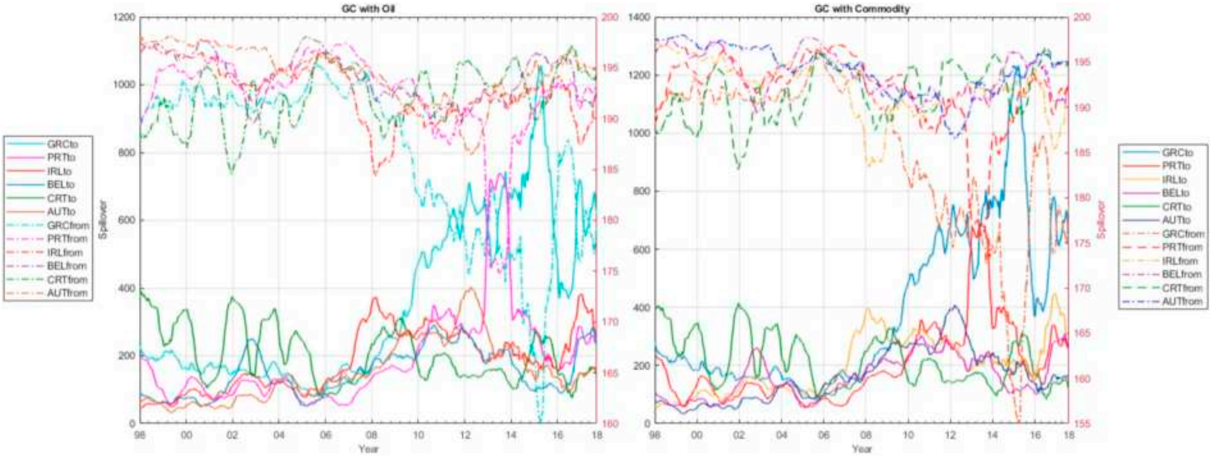


Fig. 6. GC spillovers [oil and commodity effect].
This figure represent the conditional spillovers with oil and commodity index as exogenous to the sample blocks. A detailed description can be found in 'Greek Crisis' subsection under Dynamic Analysis.

The swings are much more substantial for India in the post Asian Crisis period.[18] For both India and the Philippines, reversions quickly followed a spike in transmissions in the burgeoning GFC period.

Interestingly, the patterns for both Singapore and South Korea unveils a key finding. The signals point out that both the markets reflect a turning point in vulnerability appearing at the same time, between 2003 and 2004. Up until this point vulnerability decelerates gradually, rationalizing the benefits of flexible policy interventions in the post Asian crisis period, where a number of IMF programs and reforms were carried out over the late part of the previous decade. Vulnerability continued to amplify past the turning points for these markets.

In the post Asian crisis the decelerating cyclical patterns in crisis transmission and vulnerability supports the emergence of AC markets as safer investment venues relative to some other markets in our sample.

6.3. Export crisis

The second panel in Fig. 1 presents the exporting (EC) markets of Germany, Chile, France, China, UK and Australia. Higher transmission and vulnerability in EC markets correspond to the aftermath of drops in exports preceded by the Russian ruble crisis in 2014 following trade sanctions and military actions. Intuitively, the export crisis may also appear from the 2016 crude oil price drop.

We account for several key features extracted from Fig. 1 in the vulnerability of systemic risks. We find a brief period of dampening that precedes further amplification for Germany at the same point as that of Singapore and Korea. Similar turning point is also detected in the Australian pattern but appearing much later. This suggests, that German transition is driven by the same force that exists for Singapore and South Korea, whereas Australian transition reflects emanating GFC. Australia sees slowly reducing vulnerability and increasing transmission over the period. A second key feature is turning points in the curves of the UK and France leading to sharp rise in vulnerability becomes apparent facing European crisis only. Finally, we detect such degree of transitions for China facing the very recent 2015–16 Chinese stock market turbulence.

The Chinese market is fraught with speculations over an ensuing crisis (Forum, 2015; Mauldin, 2017; Elliott, 2017; Chiang et al., 2017; Mao, 2009). The speculations are fuelled further with the building up of 2015–16 stock market crash preceding a pronounced rise in both vulnerability and transmission. Moreover, with relatively low vulnerability and high transmission during GFC, Chinese market established exemplary resilience.[19] With the recent deterioration of Chinese resilience casting risks in Chinese stock markets within systemic risk framework requires further examining before we postulate China to be the ground zero for the next global financial crisis.

6.4. Oil exporting markets

Now we explore the impact of exogenous factors such as oil indices into the system by examining the changes brought about as well as for robustness in the transmission and vulnerability dynamics for both AC and EC clusters in Fig. A4.[20] We account for the

[18] Indian data is sourced from Bombay Stock Exchange (BSE). BSE is not only the largest in the world in terms of a number of listed companies, it is also in the top 10 in terms of market capitalization.

[19] This may be presumably due to China's strongly growing domestic economy and timely policy interventions contributing in the economy going upstream facing the Global Financial crisis.

[20] See online Appendix A, Fig. 4.

heightened systemic risk between China and Germany leading to other EC markets in Fig. 1 with robustness delivered in Fig. 4. We find that oil inclusion results in systemic risk stemming more from France and the UK than others. Turning to AC markets in the other panel of the same figure, we do not find any substantial up or down swings for the AC markets with the inclusion of exogenous factor. This suggests, Asian markets have better resilience to oil shocks than other markets within a systemic risk framework.

We show the spillovers of the OED and the OEE markets (OED comprises the USA, Canada, Russia, Norway, Japan and New zealand, while OEE includes the Saudi Arabia, Israel, Iraq, Sri Lanka, Nigeria and Venezuela) in Fig. 2. Again, we compare Fig. 1 for robustness including oil in Fig. 5.

We find acute swings in transmission and vulnerability for Oil Exporting Developed markets highlighted in Fig. 2. With the exception of Japan, this holds for Venezuela,[21] the USA, Canada, Russia and Norway. We find both Venezuelan and Russian transmissions exceed the aggregate levels during the episodes of US-led Iraq invasion; in the unveiling of GFC, throughout the European debt crisis and the recent Russian ruble Crisis. We also find that despite continuing increases in Venezuelan amplitudes, resilience in the Russian market intensifies. Additionally, Norwegian market resilience remains stronger relative to the aforementioned markets, but weaker than that of the USA and Canada.

Turning to OEE markets plotted in the second panel of Fig. 2, we observe that since the Iraq invasion, Saudi Arabia and Israel have been the highest transmitters and recipients of return shocks, particularly in the Middle East. While only a few cycles of transmissions and vulnerabilities are discernible for Saudi Arabia and Israel during the outbreak of GFC, these pick up dramatically during the period of plunging oil prices in 2016. In the following years vulnerability increases for the Saudi Arabian markets. The remainder of the markets in OEE and OED clusters have been less resilient since the GFC with increasing systemic risk, similar to the results for the EC and GC markets.

The results for including oil shocks in these groups are presented in Fig. 5. We find stronger fluctuations of transmission/vulnerability for Iraq, Kuwait, the Saudi Arabia, Israel, Norway and Russia. Moreover only to Venezuela, Norwegian swings exceed that of the others in these clusters. While Norway shows heightened vulnerability to oil shocks in recent times; prior to the invasion of Iraq, Iraq's responsiveness to oil shocks were highest.

Our results support heightened fragility in energy exporting markets, heralding an increase in systemic risk. We do not find any dampening in the spillovers with the inclusion of oil shocks in Fig. 5.

6.5. Greek crisis

A major crisis since the Global Financial Crisis is the European debt crisis, erupting in late 2009, finding its way to major European markets. Studies in this vein suggests, the crisis spread quickly, even before policymakers became aware of the serious troubles facing the European markets; see for example (Jolly and Bradsher, 2015; Mink and De Haan, 2013; Arghyrou and Tsoukalas, 2011; Jolly and Bradsher, 2015). In Fig. 3, we present the dynamic analysis for the GC cluster. Greek, Irish, Portuguese, Croatian and Belgian systemic risk estimates continue to amplify up until 2016. The transmissions for all the markets remain high. In essence, we identify an overall upward shift in the transmissions of GC markets over the 20 years, with heightening vulnerability for Greece, UK, Ireland and Belgium in recent times.

Aiming to explain resilience in the GC markets, we point out key features in vulnerability. Vulnerability remained upstream for Greece, Portugal and Ireland up until the post European Crisis period. We detected a brief dampening in vulnerability only to be picked up much more substantially facing the smaller crises emerging in the post European crisis. The recent jump in vulnerability is the highest amplification that heralds a crisis may emanate from within the GC cluster.

The results complement Ghulam and Doering (2017) by identifying higher connectivity of GC markets to EC, OED and OEE markets. The gyrations in GC markets suggest that crisis conditions have not subsided for this cluster. The picture that emerges suggest that a larger crisis may erupt from Greece or other GC markets.

Including Oil and Commodity in Fig. 6, we record amplification in overall transmission and vulnerability. This cements the robustness of our analysis while suggesting that GC markets are vulnerable to exogenous shocks to a lesser extent than that of EC, OED and OEE markets.

We again find a turning point of similar degree from dampening to magnification appearing for Belgium at the same time as Germany, Singapore, Korea and some other markets. Next we explain what causes these transitions in vulnerabilities to appear together.

6.6. Conduit effects

We detected vulnerability transitioning from dampening to amplification for Germany, Singapore, South Korea and Belgium appearing at the same time in the beginning of 2000 in Figs. 1–3. We aim to present rationalization for such collinear movements in vulnerability.

In Fig. 2, we find the same turning point in the vulnerability curve appears for the USA and Japan at the same time with aforementioned markets, but to a much higher degree then others. BIS (1998) summarizes that the USA and Japan were found to be conduits if not ground zero for earlier crisis events. In light of this discussion, we have detected the conduit effects of the USA and

[21] Chen et al. (2002) suggests Venezuela is an important representative of Latin American markets. Up until 1999 there was no visible diversification in Venezuelan market due to its high level of integration with other Latin American markets.

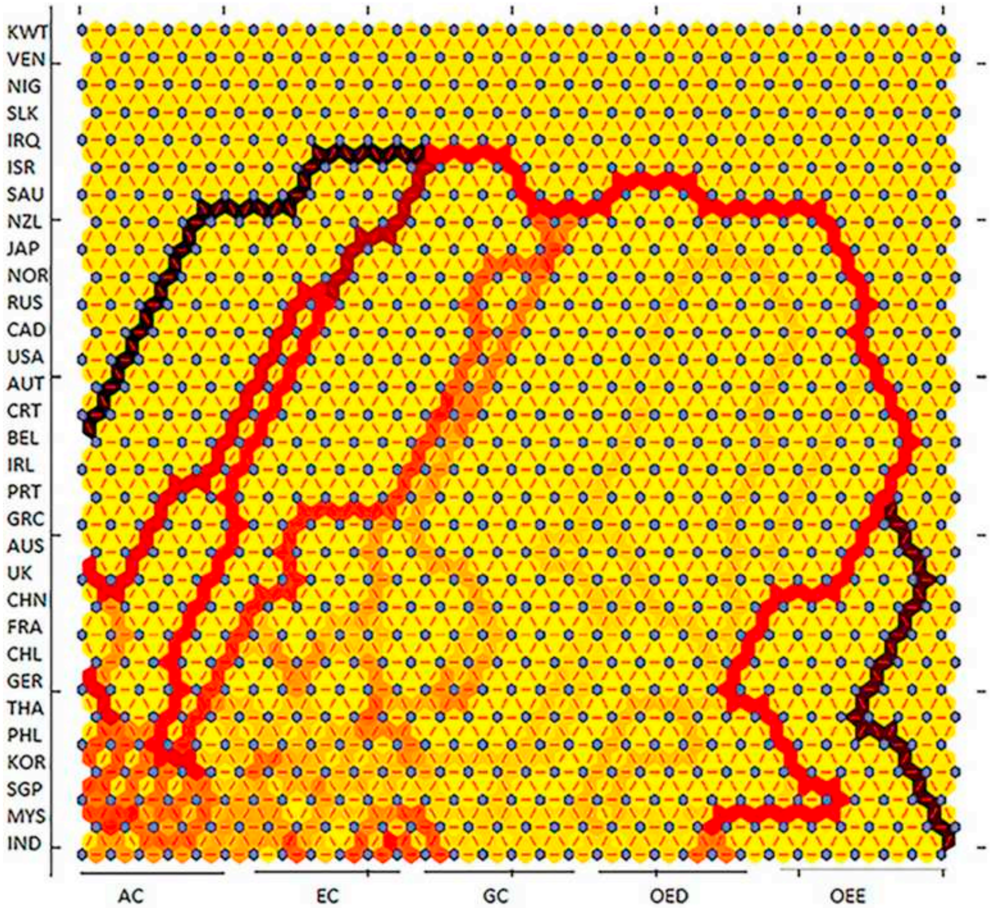


Fig. 7. Crisis-Map (full sample period). Maps generated with SOM gauging raw data from DY unconditional spillover transmission measures with 70–30 splits on the full sample period for all vectors. A detailed description is outlined in 'Crisis Maps' section.

Japan to Germany, South Korea, Sri Lanka, Belgium and Australia. The crises that transpired in the USA from dot comm bubble and the subsequent energy crisis has exerted transitions from low to high vulnerability regions for Japan, South Korea, Singapore, Germany, Belgium and Australia. This may be due to high volume of trade between these markets with the USA and also with Japan at some point. In short, we have captured the conduit effects outlined in Baur and Schulze (2005).

7. Crisis maps

We now take the DYCI spillover indices generated in the previous section as inputs to produce crisis maps in the form of Self-Organizing Maps.

Using DYCI as the raw input data rather than historic returns or financial indicators as in earlier papers (Marghescu et al., 2010; Sarlin and Peltonen, 2013; Betz et al., 2014) or log prices in (Resta, 2016) we are able to provide a new way of examining systemic risks, highlighting the interconnectedness and spillovers of the system particularly in representing the paths of vulnerability in the system.

Our main contribution is to present meaningful visualizations of high dimensional inputs. The generated topology of the markets illuminate hidden overlapping and non-linear dependencies. Such technical representation is achieved by defining the topology with SOM Best Matching Units (BMU) discussed earlier.

An important novelty lies in our dynamic (windowed) mapping approach. We disaggregate our original map to thirty-nine (39) successive maps, sampling at roughly 135 rows (semi-annually) for each iteration. We extend the number of replications until all the 5041 rows are mapped. This approach allows us to visualize and examine the changing degree and direction of contagion during different crisis. What lies closest to the spirit of this paper is León et al. (2017) proposing hierarchical clustering of estimates derived from indirect networking methods.

Fig. 7 presents the full-sample crisis map generated with SOM using unconditional spillover measures. The horizontal and vertical axes present the markets individually and in clusters. The representation is similar to a heat-map with reordered column positions. The degree of crisis is depicted with lighter to darker colors. The classifications lie between no events (when the convergence in loss function is successful) to events (when loss function is not optimally minimized for as non-linearity heightens in places). Crisis transmission is drawn along the path of events across contemporaneous market links. Additionally, the transmission pathway separates changing stress levels naturally clustered together for all data points.

We interpret the graphs as following. The darker colors represent fissures in a plateau of the mid-colors with occasional lighter colored higher features. To continue the analogy if we consider a shock as some form of flash storm somewhere in the system, then the fissures represent the path into which the storm-water will drain. Deeper fissures will attract more water. This refers to the areas that are most vulnerable. The pathways visible on the plots represent the path of least resistance for shock transmission through the system. For example, in Fig. 7, it is clear that the markets from South Korea to Israel on the map are highly vulnerable to a shock from the US (shown on the horizontal axis). We see topographic depressions are deeper as the fissures run across GC to OED clusters. Depressions are deeper again as the crack runs through EC to AC cluster. The dislodging on the plateau forming the fissure represents the vulnerability pathway in the system carrying crisis across the system. Here, Fig. 7 gives us a parabolic pattern in the fissures pathway that connect the major topographic depressions. Now we are presented with the question if these fissures are more ephemeral than long lasting.

All these figures representing dynamics in crisis maps over nearly two decades, breaks down to semi-annual time periods in Figs. 8, 9, 10 and 11 to show the evolving vulnerabilities of the financial networks. In the first half of 1998, during the Asian crisis, there is a substantial web of fissures connecting many markets in the system. The vulnerability of the system to shocks is evident. This begins to ease in the second half of 1998 and into 1999. Throughout 1999 and 2000, the activity transmission loops at the right hand side of the figures are especially apparent. These maps show the high vulnerability of the OED markets, and increasingly the AC markets to shocks originating from the EC markets. Interestingly, there is little vulnerability to transmission from the US across markets either before or after the dot-com crisis (with the exception of Australia). By 2004, vulnerability to US sourced shocks evinces as a source of global vulnerability (on the left hand side of the figures) and this continues right up until early 2007. However, this does not identify the most vulnerable pathway. Instead, by 2007 markets are most vulnerable to shocks emerging from the EC countries. This possibly reflects the anticipated effects on their economies of the slowdown of the booming demand for exports due to high growth in Asia, perhaps as an indirect consequence of the reduced activity in the US following the crisis. For the following years the primary source of vulnerability in the system remains around the role of shocks from EC markets, and with shocks that affect those markets themselves (across the top of the figures).

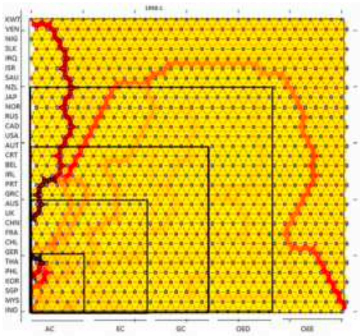
Although we have presented how vulnerability pathway, or in other words, crisis transmission pathway in analogy to storm water mounds change along the web of fissure across the plateau, we have detected a common parabolic pattern in the fissures running from end to end throughout the plateau (the system). More coverings open up as new events are triggered and the bedrock is riddled with openings in major events, the running of storm water, drawing an analogy to crisis transmission is temporal. The new cracks fill up quickly, and the system remains with the common pattern in the pathway of crisis transmission over the entire sample period. This is a new finding presented for the first time in the vein of crisis prediction.

There are interesting small surges of vulnerability evident in hot-spots, which we denote sinkholes, in a number of the figures. According to Davis et al. (2010); Khandani et al. (2013) an adverse feedback loop spreads across sectors as deadly doom loop (Farhi and Tirole, 2017) and across international equity markets as diabolic loop(Brunnermeier et al., 2016). We visualize crises spreading across different clusters in the system as a feedback loop completes circle within a cluster and find such sinkholes appearing in the system in 2004:1 for GC, 2004:2 for OED, 2006:1 and 2006:2 for AC, 2008:2 for GC, 2012:2 for EC and 2014:1 for OEE. Moreover, we find multiple sinkholes appearing in the maps for 2009:1 for GC, OED, OEE; 2010:1 for GC and OED; 2016:2 for EC. However, we are faced with the question on the importance of these sinkholes. Are these sinkholes random appearances? Can we predict crisis forming from these sinkholes?

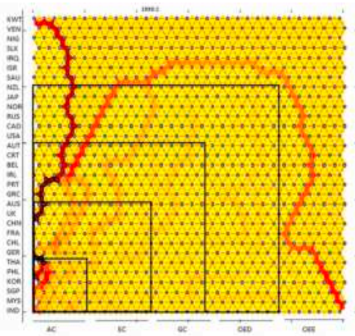
As per Brunnermeier et al. (2016) diabolic feedback loops transmit risks across capital markets as cascading common equities pooled in SIFIs, indicates a buildup of crisis across national borders. This in turn results in a global contagion. Turning to the first half of 2006, we detect sinkholes creeping up into the system. Can we expect that we will see crisis erupting in the following period? We see rapid dislodging on the plateau in the next period. Moving along, we show new web of deeper fissures opening up along with new sinkholes facing the GFC in 2007. Further, the parabolic pattern in the fissures pathway prevalent in calm times, is overlain with many new fissures. Crisis transmitted everywhere along the path of the common pattern. As the effect of crisis subdues, we see these new deeper fissures are filled up and the common parabolic pattern or the common fissure resumes. Again, in 2008 and in 2010 we detect unanticipated sinkholes emerging in the plateau. In both cases, the following period brings in many new openings and fissures with voids exceeding normal times leading to major crisis erupting throughout the system as heightened vulnerability is spread across the system. In the first case, we see a sudden spike in ongoing crisis, and we are faced with the European crisis in the latter case. In all cases examined, we conjecture that the openings into random sinkholes heralds imminent crisis and heightening of transmissions across the system. In the dissemination of a crisis event, the system reverts back to the common parabolic pattern. This is a new presentation in this vein of studies in terms of both long term persistence of commonality in transmission pathway and early warning system.

In contrast, we also capture strong endogenous crisis transmission in our system of dynamic mapping. For example in 2009:1 a strong vulnerability is revealed for AC markets and oil exporting emerging markets, with the sources from the USA, Australia, and India. In 2010:2 there is vulnerability for the USA and Australia from the Asian markets. This is consistent with the resilience of the Asian markets in resisting the effects of the Greek and European debt crises.

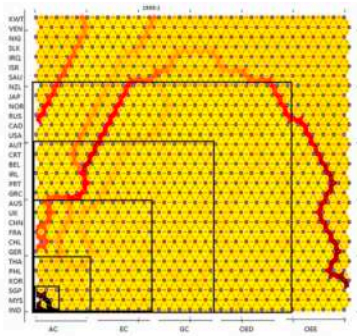
In our DY spillover analysis, the total spillover index reached an all-time high for China. A number of papers focused on China as a potential source market (Chiang et al., 2017; Forum, 2015; Elliott, 2017; Mullen, 2017; Mauldin, 2017; Forum, 2015; Cheng, 2017). However, the full visualizations in the crisis maps do not support the conclusion that China is the source of vulnerability in the



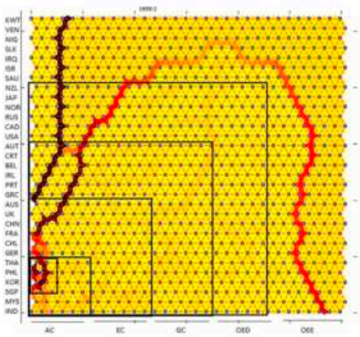
((a)) 1998:1



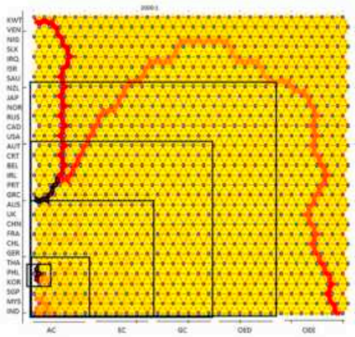
((b)) 1998:2



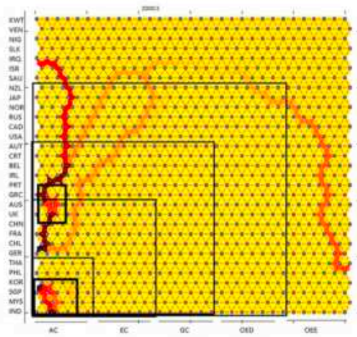
((c)) 1999:1



((d)) 1999:2



((e)) 2000:1



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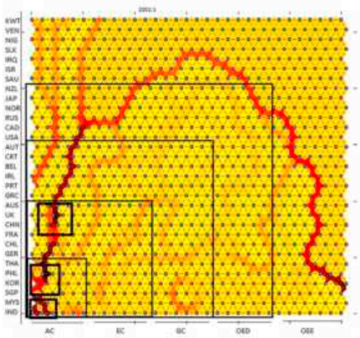
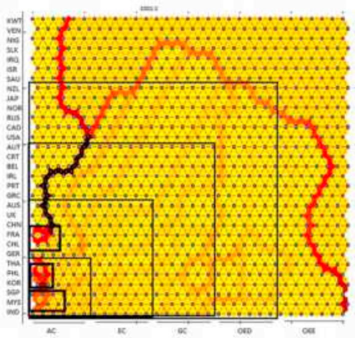
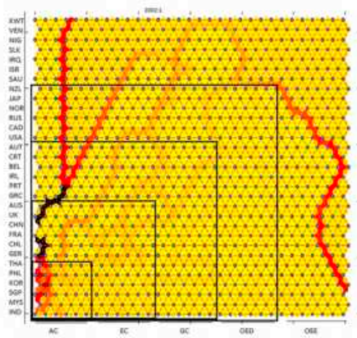


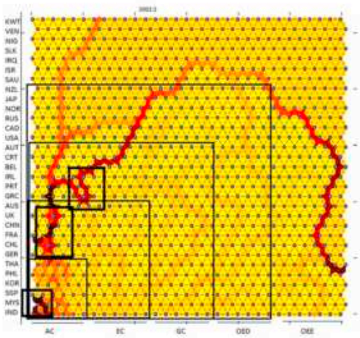
((g)) 2001:1



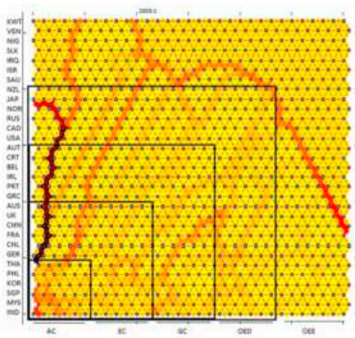
((h)) 2001:2



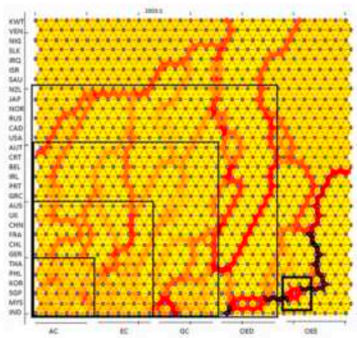
((i)) 2002:1



((j)) 2002:2



((k)) 2003:1



((l)) 2003:2

Fig. 8. Dynamic crisis transmission maps from 1998 to 2003. Maps generated with SOM gauging raw data from DYCI transmission with 70–30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.

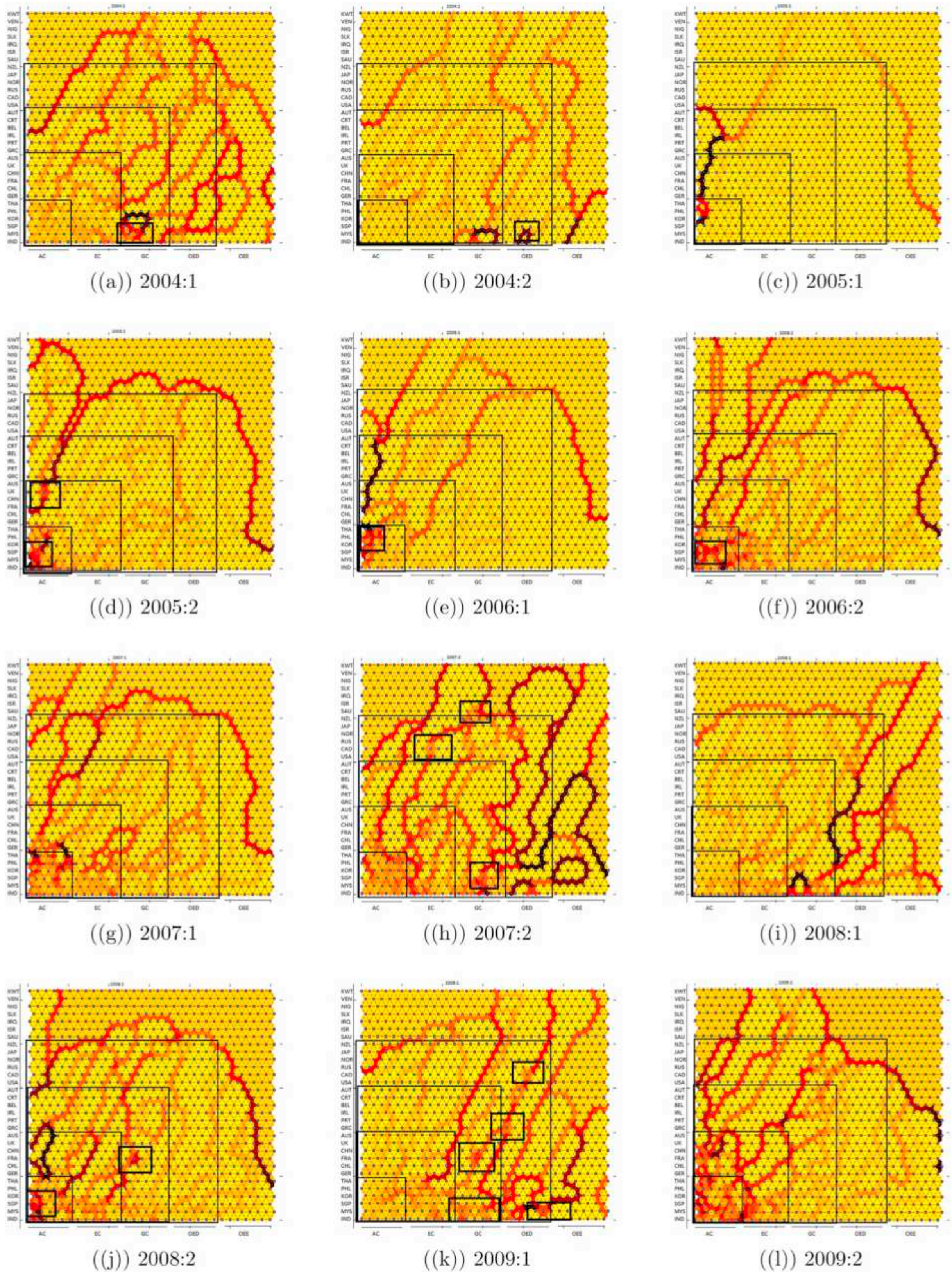
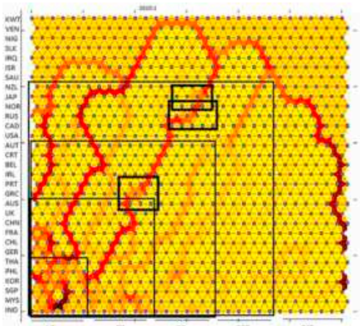
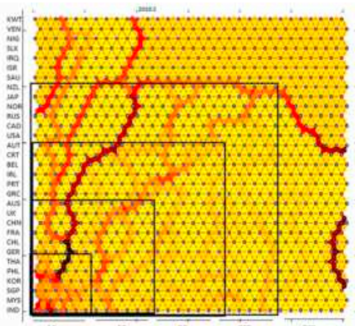
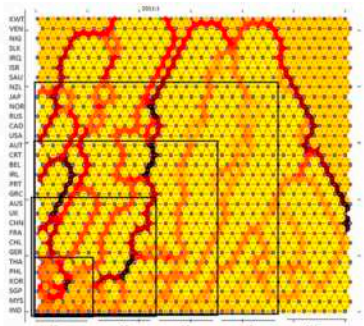
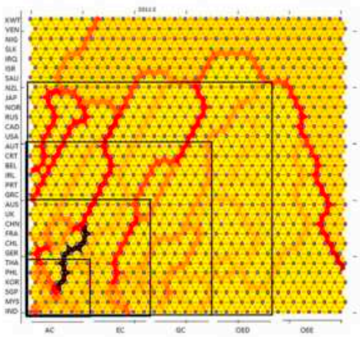


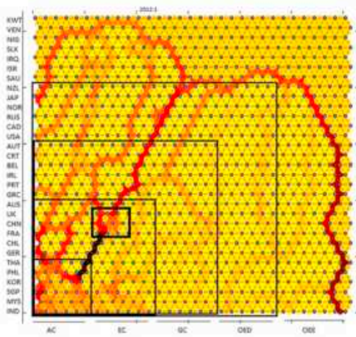
Fig. 9. Dynamic crisis transmission maps from 2004 to 2009. Maps generated with SOM gauging raw data from DYCI transmission with 70–30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.

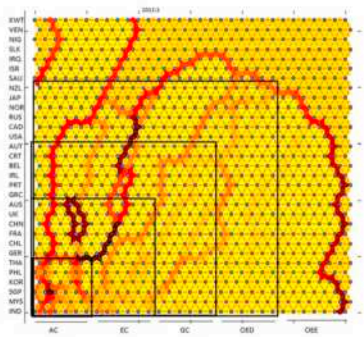

((a)) 2010:1

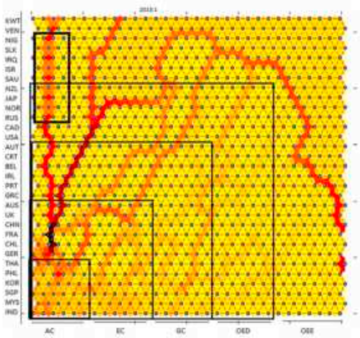

((b)) 2010:2

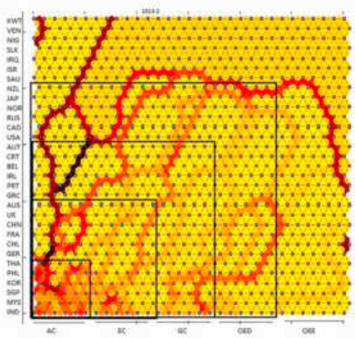

((c)) 2011:1

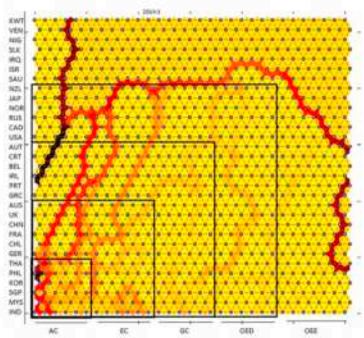

((d)) 2011:2

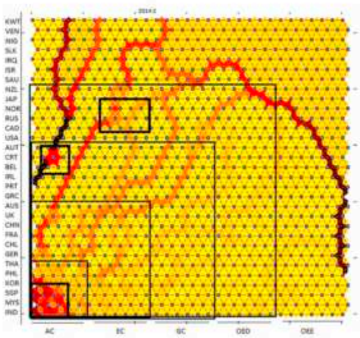

((e)) 2012:1

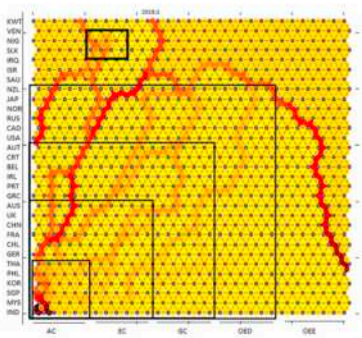

((f)) 2012:2


((g)) 2013:1


((h)) 2013:2


((i)) 2014:1


((j)) 2014:2


((k)) 2015:1

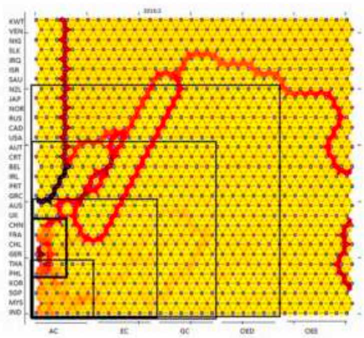
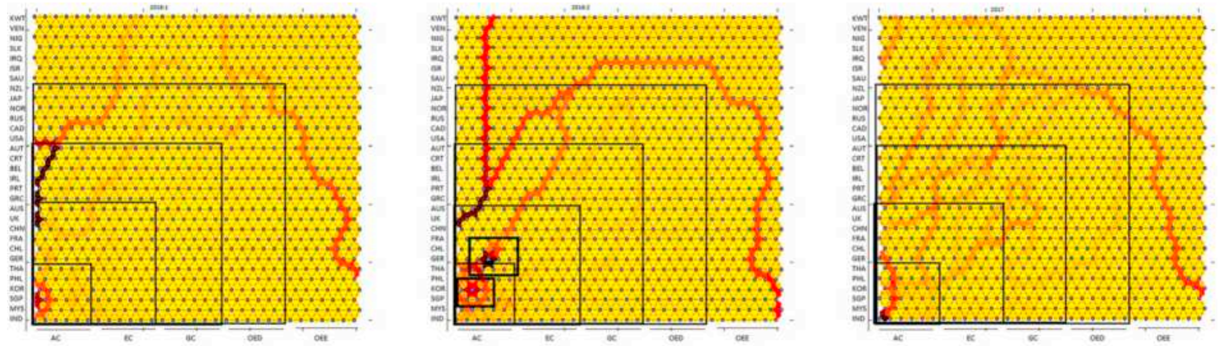

((l)) 2015:2

Fig. 10. Dynamic crisis transmission maps from 2010 to 2015. Maps generated with SOM gauging raw data from DYCI transmission with 70–30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.



((a)) 2016:1 ((b)) 2016:2 ((c)) 2017:1

Fig. 11. Dynamic crisis transmission maps from 2016 to 2017(Crisis Prediction). Maps generated with SOM gauging raw data from DYCI transmission with 70–30 splits on sub-periods. A detailed description is outlined in 'Crisis Maps' section.

system, in fact they point more towards sensitivity to shocks from the GC and OED markets. In February 2018, this view was vindicated in the rapid transmission of shocks from the US sourced shocks to the more developed markets of the world (corresponding to significant drops in Dow Jones), reflected in the predictive patterns in the crisis maps produced for 2017:1.

A complete counterfactual analysis results for dynamic spillover section and for the crisis maps are presented in online appendix section B.

8. Policy implications

One of the most appealing features of the crisis maps is that they are able to display the changing nature of vulnerabilities within a financial system in a readily accessible manner. Despite the usefulness and wide range of applications for the DY adjacency matrix approach, complementary information can be obtained from crisis maps in terms of both the amplification of spillovers and the emergence of specific areas of vulnerability.

The rolling spillover indices and the crisis maps both show that the system can move dramatically. Consequently, the range of tools required by policy makers and portfolio managers needs to be wide. In some instances shutting down a link between two markets may protect other markets, but the results of our counterfactuals suggest that the effects on the overall crisis map are not easily detected. Diagonal fissure lines across the system result from cascades of shocks sourced at an origin market and traveling on via the fissures in the system (eg US to Australia to Japan). The crisis maps highlight both the direct and indirect nature of these relationships and as such co-ordinated actions may be an appropriate means to short-circuit a crisis. For example, by blocking a pathway, perhaps through policy options such as short sales constraints, or short-term capital movement restrictions.

In other cases sink-holes emerge. These are hot spots where there is a high level of vulnerability for an individual market (or small number of markets) to shocks from a single source (or small set of sources). In this case an apt policy response may be to develop a domestic response to the cause of that vulnerability – possibly involving the traditional repair of macroeconomic fundamentals such as proposed in first generation crisis models; see, for example Eichengreen et al. (1996); Eichengreen and Hausmann (1999); Bordo et al. (2001).[22]

9. Conclusion

In this paper we present return spillover connectedness between major global markets split into multiple categories based on their size, structure and roles played during major financial crises periods. First, we make use of unconditional spillover measures to analyze static networks of markets, and conditional spillover measures to analyze changing interaction of dynamics between major markets. Our analysis not only captures the degree and direction of the episodes affecting 31 international equity markets in the past 20 years, but also allows us to explain how the strengthening of networks are responsible for uncertainties.

This paper proposes a unique way of visualizing the changing vulnerability of a financial network via automated neural networks (ANN), and by filtering on the largest vulnerabilities provides crisis maps. These crisis maps highlight the least resistance shock transmission pathways at any point in time. We show how ANN methods relate to the commonly understood VAR representation and hence can be cast as an extension of the Diebold and Yilmaz (2009); Diebold and Yilmaz (2014) approach.

Time shots provide 'crisis-maps' that detect the changes in vulnerability for markets over time. Not only do we present a complete 'crisis-map' showing a conceptual pathway for shock transmission, but we also give time varying patterns by presenting stepwise windowed stress grids.

We investigate several issues that are central to scientific discourse in the systemic risk tenet of studies. First, we provide evidence of timely intervention leading to reduction of vulnerability for many markets in the past. Second, our results reflect that changing

[22] Alternatively the cause may be vulnerability to structural issues such as high reliance on remittances.

interaction between markets are inducing transmissions that were considered vulnerable in the past, while postulated risky markets are not transmitting risks Third, we demonstrate that AC cluster is more resilient then before. Fourth, we conjecture that cutting links off may increase resilience for some countries in some scenarios. In so doing, the aberrations caused in the system instigates larger and quicker crisis transmission in most simulations. Fifth, we account for a common and persistent pattern in the pathway of shock transmission that is only disrupted with the eruption of strong crises. Finally, we propose a robust way of crisis prediction serving as early warning of crisis. Taken together, these results confirm that the countries in a system alone cannot slip out of an imminent crisis. Crucially, all countries in a system need to come together in order to short-circuit an emerging crisis.

The ‘crisis-maps’ highlight both the vulnerability and resilience dynamics in the markets examined. With an eye to practical applications, the maps presents an opportunity for investors and financial managers to diversify wealth better, enabling them to predict riskiness patterns in their portfolios. Additionally, our dynamic mapping method of channels of potential vulnerability enables policymakers to adopt proactive measures. Despite arguably underestimating the importance of interconnectedness in the pre-GFC period, policymakers have since realized the importance of identifying and co-ordinating their responses to vulnerability to crises originating elsewhere (León et al., 2017). The patterns observed in the crisis map are a means of visualizing vulnerability to policymakers, who may then base their decisions regarding actions towards channels which might be worth restricting or encouraging, to protect individual markets from unfavourable shocks. These tools may help to capture the complexity of the changing nature of integration of world markets.

Our aim is to convincingly implement means by which crisis mangers can simulate the effect of alternative intervention paths in a network and have some knowledge of where the most effective interventions may lie given the structure of the network at any point in time. Thus, we specifically acknowledge the conditional nature of the problem, and that intervention strategies may need to be flexible and time-varying, responding to the changing structure of the network and the many alternative possible sources of shocks[23].

Acknowledgement

Dungey and Volkov acknowledge funding from Australian Research Council (ARC)DP150101716. We are grateful for comments from discussant and participants at the 2018 FIRN PhD Symposium in Brisbane, Australia.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pacfin.2019.101255.

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